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An analysis of spatio-temporal landscape patterns for protected areas in northern New England: 1900–2010

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Abstract

Context

Landscape ecology theory provides insight about how large assemblages of protected areas (PAs) should be configured to protect biodiversity. We adapted these theories to evaluate whether the emergence of decentralized land protection in a largely private landscape followed the principles of reserve design.

Objectives

Our objectives were to determine: (1) Are there distinct clusters of PAs in time and space? (2) Are PAs becoming more spatially clustered through time? and (3) Does the resulting PA portfolio have traits characteristic of ideal reserve design?

Methods

We developed an historical dataset of the PAs enacted since 1900 in the northern New England region of the US. We conducted spatio-temporal clustering, landscape pattern, and aggregation analyses at both the landscape-scale and for specific classes of land ownership, conservation method, and degree of protection.

Results

We found the frequency of PAs increased through time, and that area-weighted clusters of PAs were heavily influenced by a few recent large PAs. PA clustering around preexisting PAs was driven primarily by establishment of large PAs focused on natural resource management, rather

than strict reserves. Since 1990, the complete portfolio has increased in aggregation, but reserve patches have become less aggregated and smaller, while patches that allow extractive uses have become more aggregated and larger.

Conclusions

Our extension of landscape ecology theory to a diverse portfolio of PAs underscores the importance of prioritizing conservation choices in the context of existing PAs, and elucidates the landscape-scale effects of individual actions within a portfolio of protected areas.

Introduction

The designation of protected areas (PAs) has been and continues to be a major strategy for conserving the world's biodiversity. For example, globally the area of PAs increased 2.5-fold between 1985 and 2008 (Jenkins and Joppa 2009). Generalized theories of biodiversity conservation and landscape ecology provide guidance on optimal spatial configuration of PAs for biodiversity protection (Margules and Pressey 2000), yet in practice conservation is implemented by many actors operating in a complex web of multiple landowners, diverse missions, and limited funding. Increasingly, in addition to the protection of biodiversity (Hole et al. 2011), PAs are expected to sustain social, environmental and economic values (i.e., ecosystem services) in the face of dynamic climatic and land use shifts. Providing protection for one type of value offers some collateral protection for others, and specific hotspots of biodiversity may be captured by PAs intended more broadly for ecosystem services (Chan et al. 2006). While the specific criteria and objectives of PAs vary widely across myriad conservation and socio-economic objectives, the principles of reserve design developed for the protection of biodiversity offer insight about how large assemblages, or portfolios of PAs, should be configured to accommodate broad demands.

Reserves, as a sub category of PAs, typically provide higher levels of protection than other PAs and are created specifically for insulating biodiversity from threats (e.g., urbanization and agricultural practices that may degrade habitat). In general, efficient reserve design emphasizes a coarse filter approach that protects larger, more contiguous blocks of land with connecting corridors between them, specifically for protecting habitat, open space, and species migration

options (Chape et al. 2005; McKinney et al. 2010). In general, larger reserves that are more circular and more connected are considered better for protecting biodiversity because they tend to have higher species richness, species abundance, lower extinction rates, and reduced edge effects, which can cause friction for some species. The ongoing single-large-or-several-small debate (SLOSS; Prendergast et al. 1999) in the conservation biology and landscape ecology literature questions whether many small patches or one large patch of PA is more effective in conserving biodiversity. To combat this duality, effective reserve design also incorporates the requirements of habitat specialists—which may not be accounted for in large blocks—and other factors such as population viability and replication.

A conundrum that perpetuates the SLOSS debate is that reserve design principles pose the *theoretically optimal* shapes of PAs without perfect knowledge of what is being protected (Forman 1995; Lindenmayer and Franklin 2002). Furthermore, the creation of reserves is inherently sub-optimal since past land use patterns, and in particular land tenure, limit the ability of conservation organizations to protect land identified by biophysical suitability and theory alone. Understanding the gap between theoretical design and actual designation of PAs helps conservationists tailor their future conservation efforts to meet specific objectives (Prendergast et al. 1999; Merenlender et al. 2009). Reserve design science is mature, but there is less guidance available for creating PAs for broad conservation objectives, including social values, ecosystem services, and natural resource management. For instance, Cronan et al. (2010) analyzed the spatial relationship between ecosystem function and socioeconomic drivers of land use in Maine (a sub-region of our study area), and concluded that both habitats and social values are underrepresented in the current PA portfolio due to a lack of integrated planning.

Landscape pattern analysis (Turner 1990; Wu 2004; Wagner and Fortin 2005; McGarigal et al. 2002; Pasher et al. 2013) is used to detect and to describe observed structures in landscape features (most commonly land cover) as surrogates for specific ecological values (e.g., wildlife habitat, species richness, vegetation, etc.) or land use (e.g., urbanization). In this technique, landscape metrics are used to assess the degree of fragmentation at the patch, class, and landscape-scales. The ultimate goal of these analyses is not only to describe these patterns, but also to correlate them with the underlying ecological processes driving them. While landscape pattern analyses generally measure the structure of habitats and land cover (Townsend et al. 2009; Seiferling et al. 2012), we have extended the technique to the structure of PAs themselves. In doing so, we presume that the protection status will generally ensure that natural land cover—as opposed to development—will persist through dynamic land use and climate futures.

Multiple and coordinated strategies for both biodiversity and ecosystem services are required and a diverse portfolio of PAs based on reserve design principles may offer the best hedge for protecting the broadest suite of conservation objectives (Margules and Pressey 2000; Foster et al. 2010; Halpern et al. 2013). Yet, there remains a lack of information about how the spatial pattern of independent conservation actions result in a meaningful network of PAs (Merenlender et al. 2004). This gap is largely due to the fact that until now, large regional datasets that contain both spatial and temporal information about conserved areas have not been available. After developing such a dataset (Meyer et al. 2014), we evaluated whether the individual actions of a decentralized land protection paradigm collectively followed the principles of reserve design. Using the northern New England (NNE) sub-region of the US, which includes Vermont, New

Hampshire, and Maine, we addressed the following questions: (1) Are there distinct clusters of PAs in time and space? (2) Are PAs becoming more spatially clustered through time, and (3) Does the resulting portfolio of PAs have landscape traits characteristic of ideal reserve design?

Methods

Study area

We focused on the NNE region because of its: (1) long history of land protection efforts (Foster 2002), (2) growing tension between expanded urbanization and the protection of land for ecosystem services (Stein et al. 2007), and (3) the presence of multiple nationally significant conservation innovations (Ginn 2005; Levitt 2005). The landscape is heavily forested and spans four ecoregions: St. Lawrence/Champlain Valley, Lower New England/Northern Piedmont, North Atlantic Coast, and Northern Appalachian Acadian (The Nature Conservancy 1999). The northern reaches of each state are dominated by privately held working forest, and since the 1990s, many large-scale working forest conservation easements have been secured, mostly through partnerships between nongovernmental organizations (NGOs) and large forest products and land management companies (Fairfax et al. 2005; Ginn 2005). Beyond these large blocks, there are tens of thousands of smaller dispersed parcels of public and private lands that are protected from development under various mechanisms. The entire region has 2.76 million ha in PAs (21.7 % of the land area), with 22.5, 29.0, and 19.4 % protected in VT, NH, and Maine, respectively (Meyer et al. 2014). Approximately half of the area in PAs is protected through fee simple ownership, and half is protected through conservation easements. The objectives of PAs

in the region broadly include conservation of biodiversity, provisioning of ecosystem services, public open space, recreation, and natural resource extraction such as timber harvesting.

Protected areas dataset

We used a recently developed spatio-temporal dataset that matched existing PA spatial datasets with new temporal information for 90 % of the known PAs in the region. We acquired spatial PA data from multiple state, federal, and NGO sources, using TNC's Secured Areas database as a baseline dataset (Anderson and Sheldon 2011). We then aggregated data for the year that each PA was protected using a combination of spatial datasets, personal communications from land trusts and other NGOs, and internet-based media searches. The dataset includes 11,451 ha in six PAs established prior to 1900, which we excluded for the cluster analysis (due to concerns about missing data prior to 1900) and included for the landscape trend and structure analyses. Complete details about the resulting spatio-temporal dataset are included in Meyer et al. (2014).

We developed two different but related derivative datasets from the spatio-temporal PAs data. First, because the spatial resolution of individual PA polygons was not uniform between data sources, we dissolved polygons by a combination of the year they were protected and a unique project identifier (i.e., the property name). We considered these polygons individual *projects*. For example, if a given conservation initiative included multiple adjacent parcels that were protected in the same year (as was particularly common for complex PAs and very large PAs comprised of multiple townships), they were dissolved as one project. Adjacent polygons protected in the same year by different entities remained independent projects. Similarly,

adjacent polygons that were protected by the same entity but in different years remained independent because they represent separate actions.

Second, we produced annual 30-m raster datasets of landscape *patches* by dissolving all PA polygons that were adjacent in a given year and then converting the data to rasters. For example, in 1990, any PAs that were adjacent, regardless of which prior year they were protected, were aggregated into a patch. In this dataset, patches effectively grew through time, and in some cases coalesced with patches that were previously nearby but not contiguous.

Spatio-temporal clustering

We used hierarchical cluster analysis, performed with the *fastcluster* package (Mullner 2013) in R version 2.15.2, to identify a series of clusters based on time and space. First, we created a distance matrix based on the year each project was protected and used that as the basis for agglomerative hierarchical cluster analysis. To identify objectively the appropriate number of clusters k, we used clustergrams (Schonlau 2002; Galili 2010) based on k means separation to identify the number of clusters that remained stable through repeated samples. After k was determined, we created truncated dendrograms to show the relationships between the top k clusters. Second, to account for the large range and non-uniform distribution of project size, we computed a second distance matrix based on both the year of protection and the area of each project, and repeated the cluster analysis. This step resulted in area-weighted temporal hierarchical clusters. We then relinked both the time-only clusters and the area-weighted clusters to each project's spatial location for mapping.

Spatial autocorrelation is a measure of the spatial dependency of objects, and can be used to determine how similar a response variable is for objects that are closer together in space (Wagner and Fortin 2005). In spatial modeling, spatial autocorrelation is often considered a statistical reality that needs to be isolated. However, it can also be used as an inferential statistic to indicate spatial dependency of a process. To determine if there was spatio-temporal clustering at the landscape-scale—which indicates whether conservation organizations tend to cluster their projects around existing PAs—we calculated global Moran's I (a common measure of spatial autocorrelation) at 10-year intervals. We first identified polygon neighbors for every project using a maximum 50-m buffer to accommodate minor interruptions between PAs, such as narrow roads and small streams. We then created a spatial weights matrix using a row-standardized approach to account for the non-uniform project size distribution. We ran the Moran's I test both for project polygons, as well as for a point sample derived from a 100-m grid overlaid on the project polygons. We also compared the observed spatial autocorrelation to results from a permutations test of Moran's I with 100 simulations and a null hypothesis of spatial randomness.

Landscape pattern

We used a three-dimensional (i.e., northing, easting, and time) kernel density method to assess the landscape pattern of PA projects through time. Using the temporal clusters identified above, we performed a retrospective kernel density analysis to identify firstorder spatial patterns of PAs. First, we calculated the kernel density for PAs protected within each time period (i.e.,

periodic kernel density), using a 100-km spatial bandwidth and a 1-year temporal bandwidth. Second, we repeated the kernel density analysis on all existing PAs at each break point (i.e., *cumulative kernel density*) between time periods to understand how cumulative land protection spread across the landscape. For the cumulative kernel density, we used a 100-km spatial bandwidth (i.e., search radius) and a 5-year temporal bandwidth, and computed the kernel density for each temporal cluster time interval. We then expressed the kernel estimate in 10 quantiles calculated independently for each time cluster to show the pattern of PAs at breakpoint years between the temporal clusters identified during the hierarchical clustering.

Landscape configuration

To assess landscape configuration of PAs by class, we rasterized PAs iteratively in 10-year intervals from 1900 to 2010, including all PAs established before the cutoff year. For instance, the 1900 raster included only the aforementioned six PAs established prior to 1900. We classified each time period raster in three different ways: (1) by conservation type, defined as public ownership, NGO ownership, private ownership with a conservation easement, or other (e.g., tribal lands), (2) by the conservation method, defined as fee-simple ownership or conservation easement, and (3) by the level of protection, defined by GAP status. GAP status is a system in the US used to identify the perceived level of protection given to individual PAs. GAP 1 PAs have a mandate to maintain a natural state, GAP 2 PAs have a mandate to primarily maintain the natural state but allow some provisions to suppress natural disturbances, and GAP 3 PAs allow extractive uses (Crist et al. 1998). GAP statuses 1 and 2 (i.e., reserves) are comparable to IUCN categories I–V; but while GAP 3 is considered protected from

development in the US it does not offer the protection necessary to be considered protected by IUCN standards (Anderson and Sheldon 2011).

We used the R package SDMtools (Vanderwal et al. 2012)—which uses landscape metric algorithms from FRAGSTATS (McGarigal and Ene 2013)—to calculate class-level and landscape-level shape and aggregation metrics for each raster in the temporal sequence. We chose metrics that would minimize the structural and behavioral redundancy shown by many landscape metrics (Neel et al. 2004) while allowing us to infer the spatio-temporal trends in PA configuration. We calculated these metrics on patches, rather than projects, to test whether as new projects are added patches are getting larger and the portfolio overall is getting more aggregated. Specifically, for each class and for all PAs, we measured: total area of PAs, number of patches, largest patch index (LPI), and aggregation index (AI). LPI quantifies the proportion of the landscape (i.e., not just the PA portfolio) made up of the largest patch of each class and is an indication of how much of a landscape is protected in one large continuous region. AI measures the degree of similarity or dissimilarity of a patch to its neighbors and compares that value to a theoretical maximum value based on the proportion of the landscape in that patch type. We used AI to describe the level of clumpiness of the PAs overall and classes of PAs in particular. Higher AI indicates that patches of a given class are more clumped (i.e., closer together) than dispersed. Landscape statistics were calculated by running the class statistic algorithm on a binary class raster of protection status for all PAs and are presented with the corresponding class metrics.

Results

Spatio-temporal clustering

The agglomerative hierarchical cluster analysis revealed seven distinct clusters (Fig. 1; Table 1)
for time period (based solely on the number of projects conducted), and eight clusters for area-
weighted time-distance matrices (Fig. 1). The time-only dendrogram had a much shorter overall
height (note the different y-scale), indicating there is greater dissimilarity between the area-
weighted clusters. The mean number of years per time cluster was 15.9, with a range of 6–23
years. For the time clusters, the most distinct period was 1964–1982, which had 669 projects
(Table 1). Looking at the second order node in the dendrogram, there are four distinct periods
with large dissimilarities, indicated by the heights of the nodes: 1900–1924, 1925–1963, 1964–
1982, and 1983–2010 (Fig. 1). While the number of years in each cluster did not vary
considerably, the number of projects in each cluster generally increased through time, with 3157
distinct projects, and an average of 186 projects established per year in the most recent first-
order period of 1994–2010 (Table 1).

Weighting the time periods by the area protected highlights the influence of large PAs on
temporal clusters (Fig. 1). The most distinct area-weighted cluster is isolated from the rest of the
dendrogram, and represents one very large working forest easement in northern Maine that
covered 309,000 ha. Other large PAs in the periods 2003–2005 and 2009 (also one large
easement of approximately 145,000 ha) are also distinct from the rest of the PAs. Seven of the
top eight area-weighted time clusters contained seven or fewer PAs, while one cluster spanned
the entire 1900–2010 period and had 5714 projects below the relatively small size threshold of

about 15,000 ha (Fig. 2). It may be useful to further separate this cluster into smaller components; however, increasing k in the cluster analysis had the effect of isolating additional thresholds of large PAs, rather than splitting this smallest category. To compensate for the large range of PA sizes, we created a log transformed area-weighted dendrogram (not shown) but it did not provide any separation beyond that of the time-only dendrogram.

Maps of the two different cluster approaches reveal interesting spatial patterns (Fig. 3). In the time cluster map (Fig. 3, left), there is a strong tendency of the recent PAs to dominate the northern portion of the study area. The area-weighted map (Fig. 3, right) shows that smaller area-weighted time clusters are distributed across the entire study area, while the larger ones are predominantly in the northern part of the region. Since the other clusters include many fewer PAs each, they appear more isolated, with the exception of the 1914–1937 cluster which is comprised of primarily parts of the White Mountain National Forest and the Green Mountain National Forest. There is a conspicuous lack of small PAs in the southern portion of Maine compared with the number of small PAs apparent in Vermont and New Hampshire. This absence may be due to some southern Maine PAs that are known to have been excluded from the baseline spatial PA dataset obtained from TNC due to privacy concerns of individual landowners. However, a related analysis of the distribution of the PAs analyzed in this study (a 90 % sample of all known PAs) showed the sample was not biased by the size of PAs (Meyer et al. 2014).

In our tests for spatial autocorrelation using global Moran's I on PA polygons, there was a general trend of increased spatio-temporal clustering of PAs through time until a peak in 1989.

This result means that PAs closer together are more likely to have been protected close in time, showing that conservation projects are clustered in both space and time. All years, except 1900–1917 and 1924, showed significant positive Moran's I values, indicating spatial autocorrelation (i.e., clustering; $p < 0.05$; Fig. 4). Significant negative values would, conversely, indicate the presence of a repulsive spatial process, which we did not observe anywhere in these data. The variance in Moran's I decreased through time, likely as a simple geometric result of having more PAs on the landscape each year (Overmars et al. 2003).

We tested the sensitivity of these spatial autocorrelation results to the neighbor distance threshold of 50 m that we used. Using a larger maximum distance between PAs that were considered neighbors (we tested the range 50 m–5 km) suppressed the positive Moran's I values slightly, but the shape of the curve in Fig. 4 with the peak in year 1989 was consistent across all permutations. Close examination of the data indicates that the large increase in Moran's I in 1950 is likely the result of a large number of town forests in Vermont, which existed prior to 1950 but became recognized as PAs in that year.

In the point-based Moran's I analysis, there was a generally increasing trend in positive spatial autocorrelation approximately until 1960, after which it undulated but mainly remained consistent through 2010. The point based analysis may not be robust, however, since the PAs have highly irregular shapes (e.g., the Appalachian Trail); thus point sampling may have biased the results for irregular PAs.

Landscape pattern

The results of the spatio-temporal kernel density analysis show landscape-scale (i.e., first-order in spatial statistics terminology) variation in PA activity during each time cluster. The *periodic* kernel density showed where on the landscape conservation actors were most active during each period (Fig. 5). There was a broadening of PA activity through time, presumably as more conservation actors (i.e., NGOs and public agencies) became engaged. Early PA activity tended to be isolated across the landscape, whereas in more recent periods, there were more hot spots distributed more broadly (e.g., Fig. 5, 1994–2010 panel). The 1994–2010 period showed a strong gradient with the higher intensity of PA activity located toward the northwest of the study area and away from the coastal population centers in the southeast.

The *cumulative* kernel density map (not shown) revealed a slightly different pattern and showed that overall PA density shifted eastward from Vermont and New Hampshire to Maine in recent time periods. Early during the study period, landscape intensity was dominated by individual PAs, while, as we would expect, now large assemblages of PAs drive landscape pattern through conservation leverage. For instance, many individual PAs in north and western Maine coalesced with the recent large-scale working forest easements in the Moosehead Lake and Western Mountains regions. The cumulative results showed a linear pattern that follows the spine of the Appalachian Mountains, perhaps as a result of the formal protection of individual parcels of the Appalachian Trail (protected by the National Trails System Act in 1968) and the high priority placed on alpine areas in general during that era in this region (Anderson and Sheldon 2011) and elsewhere (McDonald et al. 2007).

Landscape configuration

Our landscape configuration results reveal several interesting temporal patterns. First, there is substantial variability in the class-specific results for each metric (i.e., protection type, protection level), but at the landscape level, the trends tend to be consistent temporally. There has been a recent rise in the total area of PAs, primarily in PAs characterized as privately owned, having easements, and having GAP 3 status (Figs. 6, 7, 8). Individual PAs typically have these three characteristics in common; however, the results were also consistent for these classes independently.

While the total area increased most sharply beginning in the 1990s, the rapid rise in the total number of patches began earlier in the 1980s, and the rate of new easement patches surpassed that of fee owned patches during the 1990s. The rate of protection of private patches with easements rose nearly 13-fold between 1980 and 2010, whereas NGO-owned and public patches increased only 5- and 8-fold, respectively (Fig. 7). GAP 1 (i.e., reserves) patches increased 1.8-fold, only slightly more than the 1.5-fold increase in GAP 2 and 3 patches combined, though the GAP 3 PAs accounted for 75 % of all patches in 2010.

The LPI analysis showed a rapid rise in the proportion of the landscape covered by the largest PA patch between 1910 and 1950, after which it remained largely flat until the 2000s. This latter increase was due primarily to a 2.8-fold increase in the LPI for privately owned patches under GAP 3 easements (Figs. 6, 7, 8). AI results revealed a consistent slight decline of aggregation across all PA patches of 2.6 % from 1900 to 1990, then a slight rise of less than 1 % from 1990

to 2010. However, a rise of 2 % in the AI for GAP 3 by itself was offset by a similar decline in GAP 1 reserve patches, suggesting patches with lower levels of protection were aggregating more rapidly than those with lower levels of protection. Interestingly, this pattern is not apparent when comparing other class distinctions, such as ownership type or method of protection, suggesting the increase in aggregation was in lower levels of protection enacted across multiple ownership types and methods.

Discussion

The goal of this project was to more broadly describe the spatial distribution of PAs in order to understand more clearly what patterns of protection emerged from individual conservation actions. We conducted a spatial and temporal analysis to evaluate how well the resulting network of PAs follows aspects of reserve design theory, as a surrogate for the potential of the portfolio to protect biodiversity. The risk of using this approach is that the intentions of non-reserve PAs are generally far broader than solely biodiversity protection, and thus achieving optimal reserve configuration is beyond the scope of many of the PAs analyzed. Also, the SLOSS debate assumes equal protection for each patch, which is not true across our study area. For instance, reserve design principles may not be important to landowners who enacted PAs that allow extractive resource management, but these PAs still provide some buffer for reserves and provide forested connectivity between reserves (DeFries et al. 2005). While the PA portfolio we assessed does not only include reserves, we found applying reserve design theory to the entire portfolio helped elucidate the collective conservation value of the actions of conservation organizations and their public and private landowners partners.

First and foremost, this region has seen a dramatic rise in the protection of land from development. Just since 1999, there has been nearly a doubling of the area protected (Meyer et al. 2014). Many diverse public and private organizations have used a variety of different tools to protect nearly 22 % of the NNE region from future development. This trend is consistent with national trends, where conservationists are not only protecting more area, but are doing it in bigger transactions and with more reliance on conservation easements (Kiesecker et al. 2005; Rissman et al. 2007; Davies et al. 2010). These strategies can spread conservation investments further than fee simple acquisition, but may be less driven by conservation prioritization than by opportunity (Fisher and Dills 2012). We found the number of patches of easement PAs is growing more rapidly than that of fee-owned PAs, and privately owned PAs are being created more than twice as fast as public and NGO PAs. In the NNE, there has been a disproportionate increase in the protection of large-scale working forests. As our results show, these conservation investments have made important contributions to the portfolio, both from a total area perspective and in the increasing level of aggregation. Furthermore, since at least one NGO or public agency typically has a legal interest in the large working forest easements (i.e., they are the holders of the easement), conservation organizations may be able to refocus some of their resources on more tightly controlled reserves of higher priority conservation, while the large easements protect larger areas from development. Therefore, our results may reveal an important interaction between the aggregating effect of large easements and the disaggregation of strict reserves.

We found evidence of both temporal and spatio-temporal clusters of protection. Using the number of PAs created, we found seven distinct periods of protection activity with shorter durations through the 1900s than the three periods previously identified (Meyer et al. 2014). We also showed that factoring in the size of projects is critical, as clusters characterized by the recent large working forest easements overshadowed the thousands of other PAs initiated throughout the time period we examined. This result is important because while the very large PAs are driving the absolute area in PAs, there is also a trend of an increasing number of projects per period. Interestingly, for the area-weighted cluster analysis, PAs under about 15,000 ha were all categorized together for the entire study period, despite obvious heterogeneity among those PAs. This suggests further analysis focused on this one cluster could reveal more trends for small and medium PAs.

More important for biodiversity than the absolute quantity of land protected, is how individual conservation decisions scale-up on the landscape. This dynamic can have important implications for future protection priorities, especially when conservation planners make decisions about whether to connect existing PAs (Beier et al. 2011), or to create important but isolated new ones. Across the landscape as a whole, the portfolio became more disaggregated from 1900 to 1990. Since then, however, PAs became more aggregated when classes of landowner type, protection level, and method of conservation are lumped. The largest PAs drove the increasing aggregation that we found, particularly for PAs with lower levels of protection. In fact, at the landscape-level, the aggregating influence of the large easement PAs with lower levels of protection offset the decreasing aggregation of other PAs—most notably reserves—starting in the 1990s. This

result suggests the portfolio is indeed increasing its overall connectivity and contagion, despite differences in class-specific configuration.

The aggregation metric we used, AI, is heavily reliant on the total perimeter of patches relative to other types of patches, so the result that the area and number of private PA patches have increased substantially since the middle part of the twentieth century when they were very sparse on the landscape is not surprising. Similarly, easements—which were not prevalent until the 1980s—have increased their AI relative to fee PAs. AI also declined sharply from 1960 to 1990 for patches of NGO-owned PAs and then rose subsequently. This finding is consistent with a great expansion in the number of land trusts during that period (Merenlender et al. 2004; Meyer et al. 2014), which would cause lots of new patches in different regions as a result of many new conservation organizations acting in their own service areas.

Our spatio-temporal cluster analysis shows "conservation leverage" in which past PAs have been built upon and expanded, creating large assemblages of PAs, as has been found elsewhere (McDonald et al. 2007). A notable example is the corridor that is emerging between the White Mountain National Forest and northwestern Maine. The spatio-temporal kernel results (Fig. 5) show that this corridor has seen the most significant protection activity in the region, and future protection is likely to continue there. The strong, positive spatial autocorrelation is evidence that PAs are not distributed randomly on the landscape, but rather are clustered around existing PAs, in a process that has been shown to enhance the habitat conservation value of reserves (DeFries et al. 2005; Joppa et al. 2008).

We cannot presume the *conservation begets conservation* process is entirely deliberate, however. Conservation organizations compete in the context of highest and best use economics when purchasing land and easements. Other factors, such as the possibility that the low cost of land in rural areas has steered conservation there, or that the nature of large parcels may force conservation organizations to acquire more land than just the area of focus, may also be influencing the result (Fishburn et al. 2013). What is clear is that prior PAs, particularly reserves, serve as cores around which additional protected land is created. For instance, our results show consistent protection intensity for the last four time periods in north central Maine where Baxter State Park itself grew through time, and then served as a core around which surrounding areas have been put under both reserve and easement protection. This core and buffer PA growth pattern is particularly clear in a temporal animation of these historical PA data (not shown here). While still strongly positive, the spatio-temporal autocorrelation has actually declined since about 1989. This relationship is likely because newer, bigger projects that were only possible in specific locations on the landscape (i.e., large working forest easements are not possible everywhere) were relatively isolated from existing PAs.

The predominance of landscape aggregation driven by large easements may bode well for the provision of ecosystem services that are provided by land managed for resource extraction (e.g., carbon; Rissman et al. 2007), but it may be detrimental to others that do not typically persist on such lands, such as late-successional forest (Della Sala et al. 2012). In the 1990s, the number of patches of easement-conserved land surpassed those owned in fee. Similarly, the number of patches with less strict protection is increasing relative to that of reserves, and the numbers of patches of each are in fact diverging. This trend cannot continue indefinitely because short-term,

unique conditions in the forest products industry drove the rise in acreage protected by easement (Lilieholm et al. 2010; Meyer et al. 2014).

The motivations and goals of the organizations contributing to this increase in conserved lands were and will continue to be diverse, although all the PAs in the portfolio share a common resistance to fragmentation by future human development. These 2.76 million ha will remain largely free from development; yet much of the area will still experience significant anthropogenic influences, such as natural resource management, recreation pressure, human-induced disease, and invasive species, to name a few. Our analyses of the spatio-temporal patterns of land protection do not address the efficacy of PAs. Ultimately, it will be important to evaluate how well the patterns of protection status actually succeed in protecting the underlying conservation values of this PA portfolio. This network will provide stepping stones and future refugia for species responding to climate change, and will serve as a backstop for increasing development pressures in the region (Foster et al. 2010).

Our analysis shows the importance of assessing new conservation opportunities in the context of the existing network of PAs. We have just scratched the surface of what new spatio-temporal information can be gleaned about land protection in the NNE. The next step should be to use landscape metrics for what they were primarily intended: to link spatial pattern to landscape processes. With such knowledge, we will be able to assess the efficacy of specific PAs and improve future prioritizations, or even reconfigure the existing network (Fuller et al. 2010). The scope of landscape process, however, should be expanded from solely ecological processes to include those that regulate ecosystem services and other socio-economic values (Bryan et al.

2011). Many of these latter values drive public support for conservation more than biodiversity and thus must be considered (Kline et al. 2004). We have extended the principles of landscape pattern analysis to understand the implications of a growing network of PAs. Future research should take a similar approach to assess the patterns in the underlying habitats and land cover types within the PA network to document the historical progress made in protecting conditions necessary for biodiversity and ecosystem service objectives.

Acknowledgments

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Figures

Fig. 1 Agglomerative hierarchical cluster analysis for the top seven clusters of the year of protection (*left*) and the year of protection weighted by the area of each protected area project (*right*). The range of years and the maximum project size (ha) are shown for each cluster, while the height of each *node* indicates the dissimilarity between the child clusters. The number of clusters for each dendrogram was chosen based on cluster separation during repeated samples of *k*-means clustergrams.
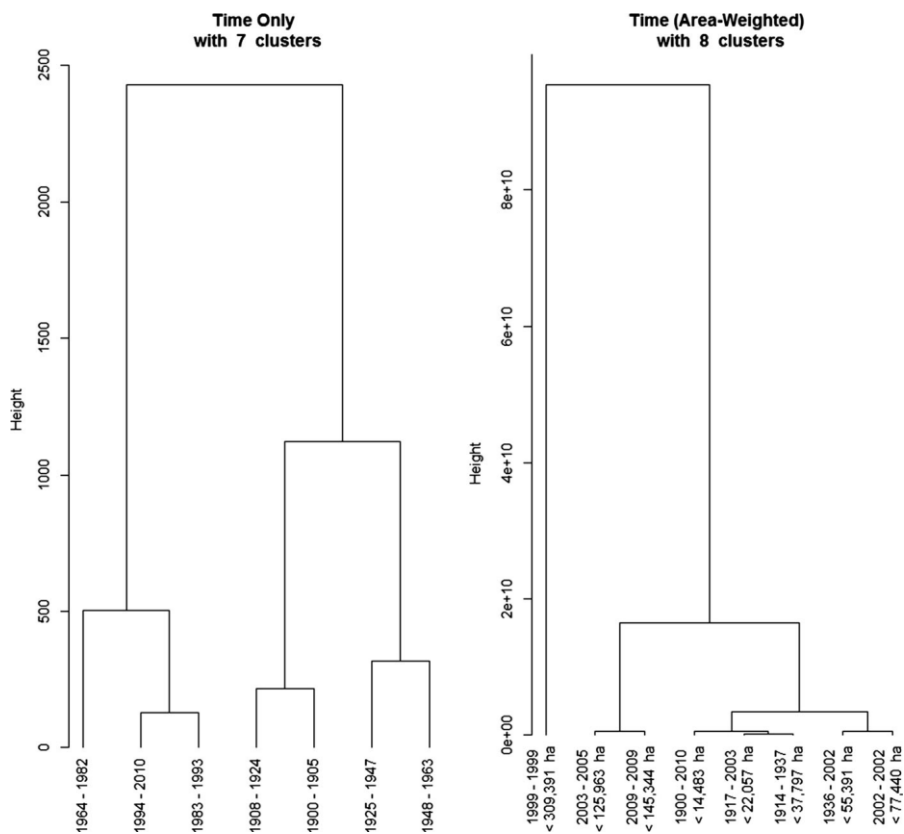
Table 1 Agglomerative hierarchical cluster analysis separated the protected areas into seven temporal clusters, showing increases through time in the number of PAs per cluster and the average PAs established per year

Cluster years	Cluster IDs	# Of years	# Of projects	Projects/year
1900–1905	7	6	6	1
1906–1924	4	19	48	3
1925–1947	5	23	145	6
1948–1963	6	16	322	20
1964–1982	1	19	669	35
1983–1993	3	11	1386	126
1994–2010	2	17	3157	186

Fig. 2 Agglomerative hierarchical cluster analysis revealed eight are-weighted clusters between 1900 and 2010. *Black points* represent the individual members of each cluster. The *grey circles* indicate the number of PAs created during that cluster, with the range of individual PA sizes expressed *below*. The maximum PA size increases along the *y*-axis.
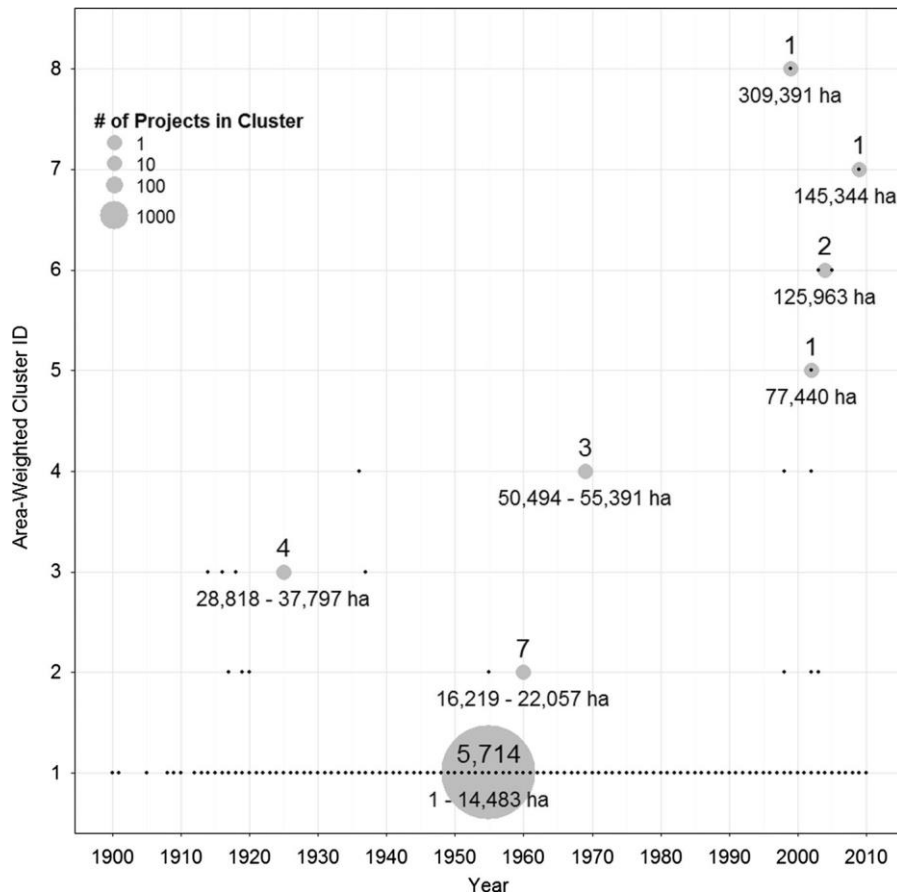
Fig. 3 Projects are shown spatially and according to their cluster membership for time-only (*left*) and area-weighted time clusters (*right*). For the area-weighted clusters, the maximum project area (ha) is indicated in the *legend*. *Darker blue* indicates more recent PAs (*left*) and larger PAs (*right*).
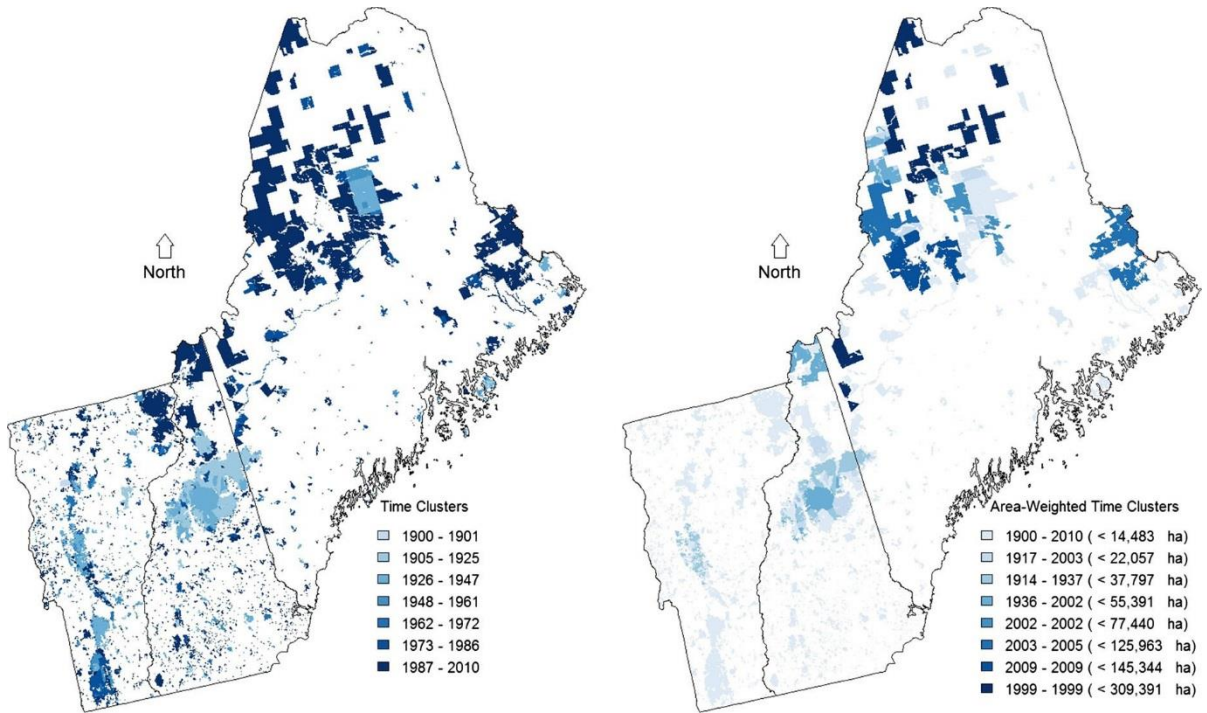

Time Clusters
- 1900 - 1901
- 1905 - 1925
- 1926 - 1947
- 1948 - 1961
- 1962 - 1972
- 1973 - 1986
- 1987 - 2010

Area-Weighted Time Clusters
- 1900 - 2010 (< 14,483 ha)
- 1917 - 2003 (< 22,057 ha)
- 1914 - 1937 (< 37,797 ha)
- 1936 - 2002 (< 55,391 ha)
- 2002 - 2002 (< 77,440 ha)
- 2003 - 2005 (< 125,963 ha)
- 2009 - 2009 (< 145,344 ha)
- 1999 - 1999 (< 309,391 ha)

Fig. 4 Spatial autocorrelation, measured as global Moran's I ($p < 0.05$), using a 50 m maximum buffer between neighbors, generally increased until 1989 and has decreased at a decreasing rate since. The years 1900–1917 and 1924 were excluded because no spatial autocorrelation was detected in those years (i.e., $p > 0.05$)
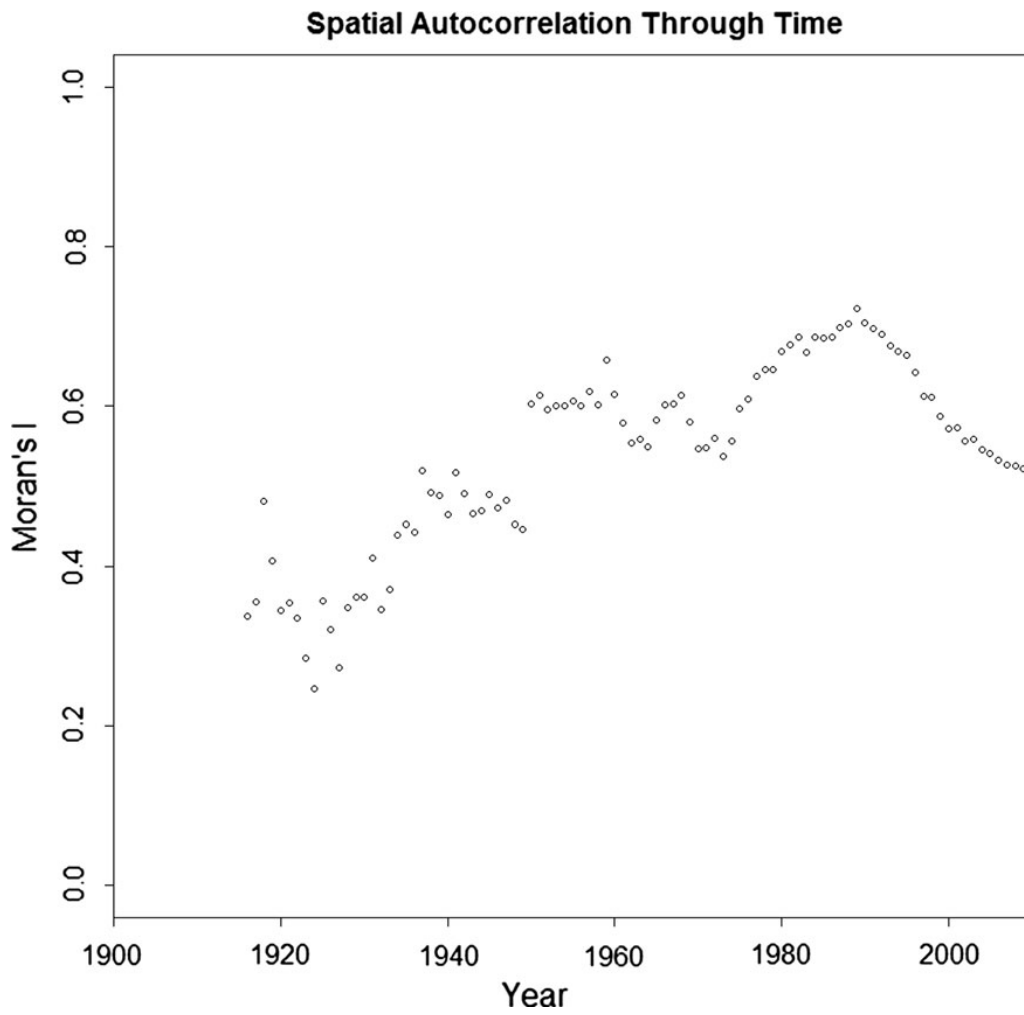
Fig. 5 The three dimensional (i.e., time–space) *periodic* kernel density, calculated for PAs protected within each time period, indicates shifting location of landscape pattern of land protection. The spatial bandwidth is 100 km and the temporal bandwidth is 1 year. *Darker red* indicates areas where protection was most active at each time interval. The time periods are based on area-weighted temporal clusters identified through agglomerative hierarchical cluster analysis. The ten quantiles were calculated separately for each period so the actual intensity in the 90 % class is not the same for each map
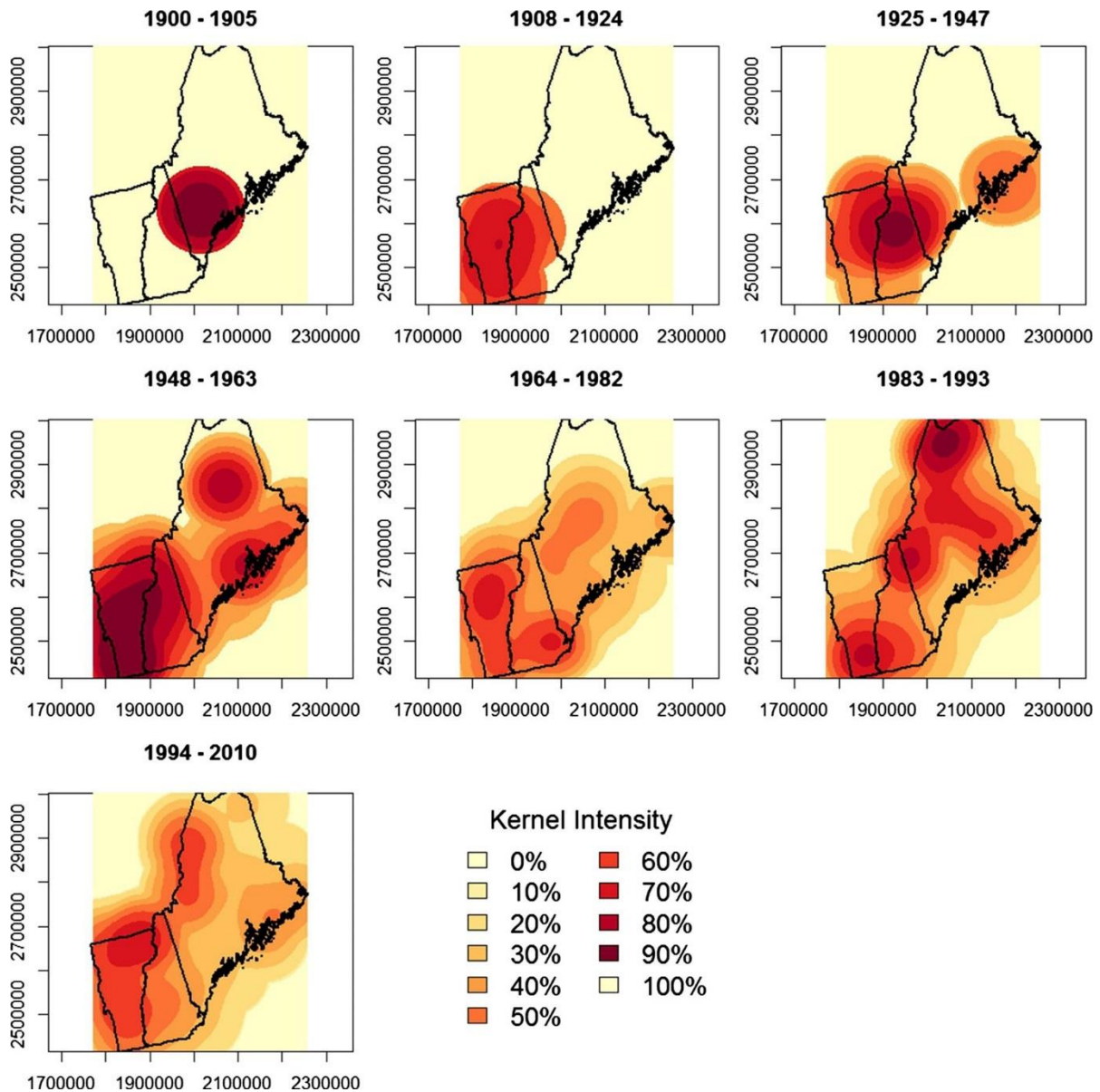
Figure 6. These four landscape metrics show the area, number of patterns, largest patch index, and aggregation index of the protected areas (PAs) portfolio through time for (1) all PAs, and separately for PAs protected by: (2) fee-simple ownership; and (3) conservation easement.
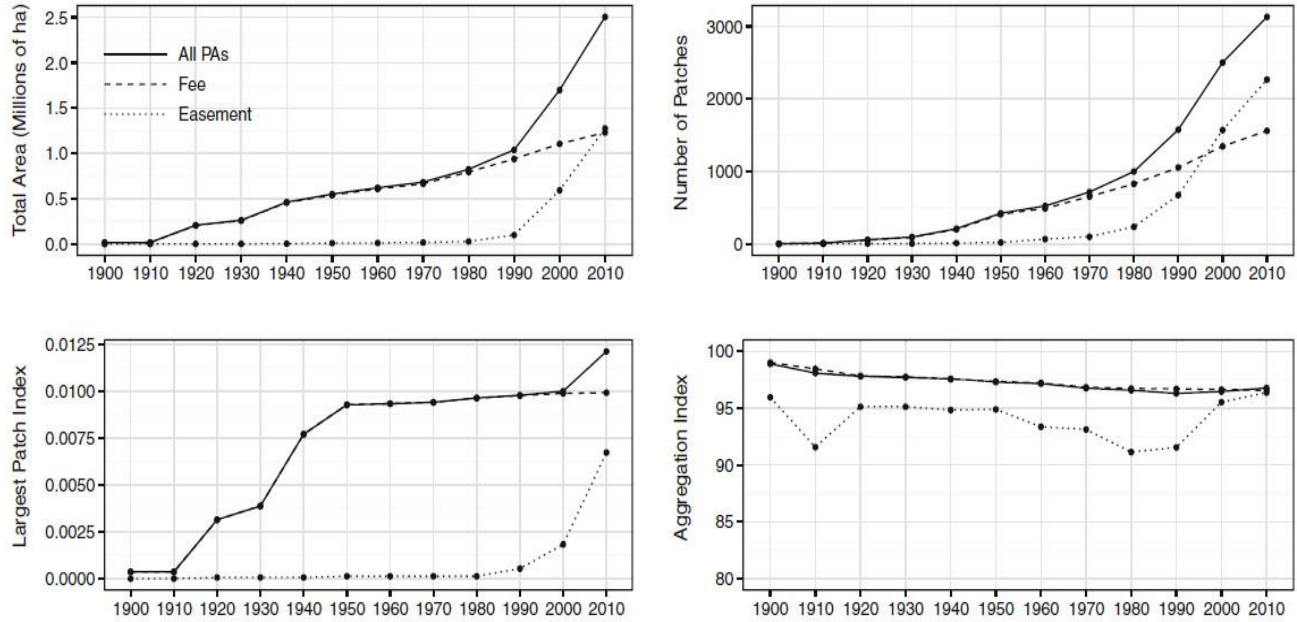

Fig. 6 These four landscape metrics show the area, number of patterns, largest patch index, and aggregation index of the protected areas (PAs) portfolio through time for (1) all PAs, and separately for PAs protected by: (2) fee-simple ownership, and (3) conservation easement

Figure 7. These four landscape metrics show the area, number of patterns, largest patch index, and aggregation index of the protected areas (PAs) portfolio through time for (1) all PAs, and separately for PAs in the conservation classes: (2) privately owned with a conservation easement; (3) publicly owned; (4) NGO-owned; and (5) all others (e.g., tribal lands).
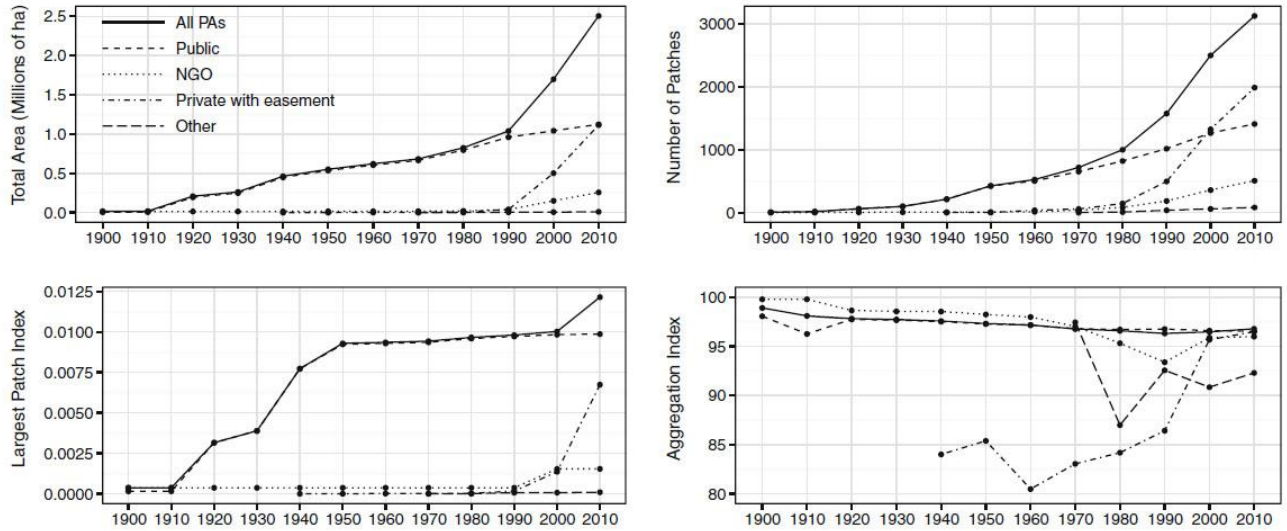

Fig. 7 These four landscape metrics show the area, number of patterns, largest patch index, and aggregation index of the protected areas (PAs) portfolio through time for (1) all PAs, and

separately for PAs in the conservation classes: (2) privately owned with a conservation easement, (3) publicly owned, (4) NGO-owned, and (5) all others (e.g., tribal lands)

Figure 8. These four landscape metrics show the area, number of patterns, largest patch index, and aggregation index of the protected areas (PAs) portfolio through time for (1) all PAs, and separately for each GAP class, where: GAP 1 PAs have a mandate to maintain a natural state; GAP 2 PAs have a mandate to primarily maintain the natural state but allow some provisions to suppress natural disturbances; and GAP 3 PAs allow extractive uses.
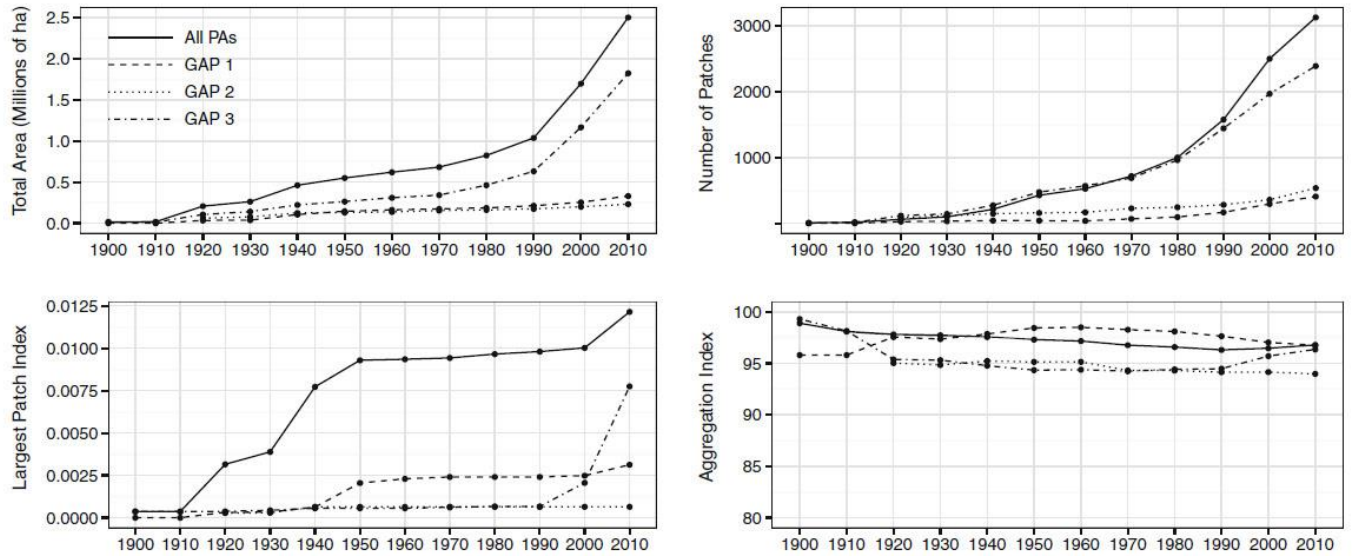

Fig. 8 These four landscape metrics show the area, number of patterns, largest patch index, and aggregation index of the protected areas (PAs) portfolio through time for (1) all PAs, and separately for each GAP class, where GAP 1 PAs have a mandate to maintain a natural state, GAP 2 PAs have a mandate to primarily maintain the natural state but allow some provisions to suppress natural disturbances, and GAP 3 PAs allow extractive uses