

1 **Title:** Scaling up conservation impact in Madagascar

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26 **Abstract:** Ten years ago, Madagascar's government committed to drastically scale up the
27 nation's protected-area coverage from ~3% to 10% of its area. We ask how successful this
28 PA expansion is likely to be in terms of reducing deforestation (and, thereby, increasing the
29 conservation of biodiversity). We statistically evaluate the impact of the prior generations of
30 Malagasy PAs and use those results to anticipate the conservation impacts of Madagascar's
31 newest PAs. We find that deforestation was reduced by the prior PAs, although by less than
32 suggested in simpler comparisons that lack explicit controls for land characteristics. Further,
33 impacts are higher where deforestation pressure is higher, which often is closer to roads and
34 cities (and which also may imply higher costs). We find Madagascar's newest PAs are sited
35 where, if managed correctly, they can achieve impacts at least as high as prior conservation.

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37 **Keywords:** Madagascar, tropical forest, biodiversity, deforestation, conservation, protected areas, siting,
38 selection bias, impact evaluation, matching

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50 **1. Introduction**

51 Held every ten years, the International Union for Conservation of Nature’s (IUCN) World Parks
52 Congress (WPC) is the global forum on protected areas (PAs). It sets the international agenda for
53 site-based protection for the decade to follow. At the WPC in 2003, in Durban, South Africa, the
54 then-president of Madagascar stunned the conservation community by embracing protection. In
55 what became known as the “Durban Vision”, former President Ravalomanana vowed to triple the
56 area protected in Madagascar before the next WPC (i.e., to go from ~3% to ~10% of the nation).
57 With this announcement came the creation of the new Malagasy PA network, i.e., the System of
58 Protected Areas of Madagascar (Système d’Aires Protégées de Madagascar (SAPM)), consisting
59 of the pre-existing PAs as well as all of the newly created PAs (Allnutt *et al.*, 2009; Raik, 2007).

60 While small in total land area, the Durban Vision was globally important. Madagascar hosts one
61 of the most biologically diverse ecosystems in the world, with a variety of endemic taxonomic
62 groups. However, despite global agreement and local efforts to conserve the region in light of
63 this biological treasure – a global public good – there have been high rates of deforestation over
64 time throughout the country (Harper *et al.*, 2007; Kremen *et al.*, 2008; Mittermeier *et al.*, 1990;
65 Scales, 2012). Such land-use changes may threaten species but they have local economic benefit.

66 President Ravalomanana’s 2003 decision to counter these threats by greatly increasing the area
67 protected was surprising in its scale but not in its purpose. For almost a century, Madagascar has
68 created protected areas (PAs) as part of achieving a balance between local need and protection of
69 biodiversity.¹ Its PA network grew steadily, since its first PA was established, in 1927. Yet forest

¹ The history of Malagasy forest conservation policy is beyond our scope. Longer accounts are provided by Toillier *et al.* (2011), Consiglio *et al.* (2006), Miller and Porter Morgan (2011), Harper *et al.* (2007), and Raik (2007).

70 area declined – due to corruption, ineffective monitoring and subsistence use of forest resources
71 by low-income rural communities (Ganzhorn *et al.*, 1997; Raik, 2007). The management of PAs
72 remained largely unchanged until the collapse of the Soviet Union in the 1980s, at which point
73 Madagascar shifted towards a more democratic style of government and foreign aid increased in
74 an attempt to stimulate both development and conservation (Raik, 2007). In 1989, Madagascar
75 ratified Africa’s first National Environmental Action Plan, creating the Association National
76 pour la Gestion des Aires Protégées (ANGAP) to manage its PA portfolio (Allnutt *et al.*, 2009).

77 Yet achieving conservation impact requires more than simply designating lands for conservation.
78 There must be 'additionality' to the actions – for example, observed deforestation post-protection
79 must be lower than deforestation would have been, at the same sites, in the absence of protection.
80 Measuring ‘in the absence’ can be difficult. However, many observable land characteristics aside
81 from protection – such as distances to roads, soil quality, management practices, or slopes – are
82 relevant to and help to indicate deforestation outcomes in any scenario. Such measurable features
83 can help to document that local development forces push back against PAs – a local constraint –
84 for instance by pushing PAs away from where agricultural or other profitability would be high.
85 Consequently, PA sites tend to be different from unprotected sites (Andam *et al.* 2008 in Costa
86 Rica, Pfaff *et al.* 2014 in Brazil, and Joppa and Pfaff 2009 globally) and, by controlling for this,
87 often we are able to get closer to understanding the true conservation impacts of PA legislation.

88 The most recent WPC in Sydney this year signaled the end of former President Ravalomanana’s
89 commitment. A retrospective analysis of Madagascar PA impacts can help to shed light on the
90 future impact of the new Durban Vision PAs. We ask: did Malagasy PAs overall generally deter
91 deforestation – i.e., one of the biggest threats to biodiversity – and, if so, do the locations of the

92 PAs appear to affect such deterrent impacts? Finally, if so, do these newest Durban Vision PAs
93 appear to be located where PAs are likely to have lasting impact? We use matching to estimate
94 PA impacts on deforestation in Madagascar – to our knowledge the first assessment of Malagasy
95 PAs with controls for location (although see Gorenflo *et al.* 2013) and including the first use of
96 matching in such evaluation (though Rosolofoson et al. 2015 provide an assessment of effects of
97 community forest management with a similar approach, implemented simultaneous to this work).
98 We assessed the impacts of PAs created before the Durban Vision, including the influence of key
99 land characteristics on the magnitude of those impacts, and then documented Durban Vision PAs
100 in terms of those characteristics. Specifically, to call attention to PAs' landscape characteristics,
101 we analyzed not only all PAs but also subsets to assess if some resulted in higher PA impacts.

102 We find that PAs created prior to the Durban Vision significantly reduced deforestation, while
103 the Durban Vision PAs were on sites that – if well managed – would yield impacts at least as
104 high as earlier PAs. Consistent with other countries (see Pfaff et al. 2009, Joppa and Pfaff 2010),
105 impacts in Madagascar can be higher when closer to roads and cities. These findings contribute
106 to global conversations surrounding expansion of PA networks at multiple scales, as the world's
107 governments strive to achieve the Convention on Biological Diversity's 11th "Aichi Target", i.e.,
108 that at least 17% of terrestrial and 10% of coastal and marine areas are effectively conserved.
109 Below, Sections 2-5, respectively, present our Methods, Data, Results and finally Discussion.

110 **2. Methods**

111 Were PAs randomly sited it would suffice to compare deforestation rates inside and outside PAs
112 to calculate PA impact. The protected and unprotected parcels would have similar characteristics
113 and thus the deforestation on unprotected lands would provide a good estimate of what would

114 have occurred at the PAs' locations had they not been protected. Many analyses compare PAs to
115 all unprotected land or to the land nearby (Joppa and Pfaff 2010a provides a review), instead of
116 controlling statistically for relevant location characteristics. When PAs differ in characteristics
117 from unprotected lands – often facing lower pressure for deforestation (Joppa and Pfaff 2009) –
118 this can lead to overestimates of the PAs' impacts. Here we address potential bias using ordinary
119 least squares regression (OLS) to understand the drivers of deforestation, and then statistically
120 controlling for biases in those drivers through OLS regression and propensity-score matching.

121 *Ordinary Least Square Regression*

122 Before getting to the matching analyses, and indeed motivating those analyses, we employ three
123 types of OLS regressions for two types of outcomes, those being where protection is located and
124 where deforestation occurs. We analyze the latter twice, starting with an analysis of unprotected
125 lands in order to see what site characteristics have significant influence upon deforestation rates.
126 We consider biophysical characteristics such as elevation, slope and distances to water, as well
127 as socioeconomic characteristics like distances to roads, villages and large population centers, in
128 addition to using indicators for large political units that differ in their geographies and processes.
129 Having confirmed the significance of those characteristics, we examine their effects on locations
130 of protection in a regression for whether land has been designated as protected. As this confirms
131 that protection is not randomly dispersed across the landscape, within a deforestation regression
132 to test for the impact of protection we will include controls for influences of land characteristics.
133 Thus, our third OLS regression is again for deforestation but considers all locations, i.e., not just
134 unprotected locations, since we want to compare the unprotected and protected locations to infer
135 the impacts of the PAs. We explain where deforestation occurs, including with a PA indicator.

136 *Matching Methods*

137 The last OLS regression considering deforestation for all locations offers one form of control for
138 site characteristics when testing the impact of PAs. We control further using matching. When it
139 is effective, matching generates control groups with characteristics very similar to treated sites.
140 That reduces the challenge of removing characteristics' influences to infer PA impact. If treated
141 and control groups have rather different characteristics, OLS may not strip out all the influences.
142 Matching focuses very explicitly on apples-to-apples comparisons, i.e., on similar characteristics.
143 Of course it can employ only observable land characteristics, i.e., assumes that conditional on X
144 (observable characteristics like slope), selection to treatment (here protection) is independent of
145 potential outcomes (Rosenbaum and Rubin, 1983; Sekhon, 2009). If protected and unprotected
146 are matched on observable covariates, they are assumed to differ only in terms of the protection.
147 For multiple continuous covariates, matching summarizes the characteristics using the predicted
148 probability of a site being treated, i.e., protected (Rosenbaum and Rubin 1983). We match using
149 that predicted probability or 'propensity score', in the sense of propensity for such characteristics
150 to lead to protection. We match treated points with the untreated points with most similar scores.
151 We also did robustness checks using calipers, i.e., rules for how similar those most similar scores
152 have to be for that treated (i.e., protected) point to be included in the analysis (we used 0.01, 0.10
153 and 0.50 as maximum propensity-score differences). For each model, we also show whether and
154 by how much the covariate balance improved, due to matching. We also address bias using post-
155 match regressions to account for remaining differences in the X covariates between the matched
156 pairs (Abadie and Imbens 2002; Rubin 1973; Sekhon 2011). Data analysis was performed with
157 R 2.13.1 (R Development Core Team, 2011) including the Matching Package (Sekhon 2011).

158 3. Data

159 3.1 Land Cover

160 The land-cover data for 1990, 2000, and 2005 that we make use of were originally produced by
161 Conservation International (CI) using Thematic Mapper (TM) and Landsat Enhanced Thematic
162 Mapper Plus (EMT+) data. CI compiled the three raster images into one multi-date image with a
163 28.5m resolution (Harper *et al.*, 2007; Kremen *et al.*, 2008). The land-cover data used for this
164 analysis was identical to the CI data, aside from minor preprocessing by Kremen *et al.* (2008),
165 noting that pixels that were obstructed by clouds during imaging for one or more of the three
166 study dates were excluded from analysis. The numbers of forested pixels that could be utilized,
167 by year, are 124,252,074 for 1990, for 2000 114,507,467 and 111,536,234 for 2005. From these,
168 we drew a random sample of 100,000 pixels for each of our two time periods of deforestation.

169 3.2 Protected Areas

170 The data we examine are a subset of the GIS file used by Kremen *et al.* (2008). We split PAs into
171 three groups by year of creation: pre-1990; 1990-1999; and 2000-2008. We refer to the latter as
172 ‘Durban Vision PAs’. Lacking deforestation data for after they were created, we infer potential
173 impact by comparing locations to PAs created prior to 2000, for which we do analyzed impacts.
174 While PAs have different IUCN (International Union for Conservation of Nature) designations,
175 the designations were not part of the dataset and, therefore, were not considered in this analysis.
176 Some locations had missing data due to being outside of the raster grid’s spatial domain. This is
177 because raster data is formed with pixels while vector data consists of points, lines and polygons.
178 The effect of these errors was minimal and the observations were removed. Table 1 shows some
179 basic statistics on PA extent, for the endpoints of our periods, and its overlap with forested areas.

180 3.3 Key Landscape Characteristics

181 Elevation data are from the NASA Shuttle Radar Topographic Mission (SRTM) and have 90m
182 resolution. We derived slope (degrees from horizontal) from the Digital Elevation Model (DEM).
183 Data for streams and other inland water bodies (i.e., rivers, canals, and lakes) came from a 1992
184 publication of the Digital Chart of the World (DCW) and Urban Area was from the 1997 DCW.
185 All DCW data has a scale of 1:1,000,000 and we note that these variables are constant over time.
186 Also constant are ecoregions, classified by the World Wildlife Fund and accessed by means of an
187 updated version of Olson *et al.* (2001) that was published in 2004. Madagascar Vegetation Map,
188 which provides the Forest Classification data, had been produced for the Madagascar Vegetation
189 Mapping Project (<http://www.vegmad.org>). The data were actually published in 2007, although
190 the timeframe of the grid is 2001 (this is not a worry as the ecoregions do not shift on timescales
191 relevant to this analysis). Here the data resolution is 30m (2007). Administrative Boundaries are
192 from the global administrative area database (GADM, Version 1). Their scale is unknown and it
193 could vary by country but, at roughly 30 Arc seconds, it is sufficiently precise for our purposes.
194 The six original provinces in Madagascar (Antsiranana, Antananarivo, Mahajanga, Toamasina,
195 Fianarantsoa and Toliara) were used as controls for regional differences, because our time frame
196 predates their 2004 dissolution (was alongside the establishment of other administrative regions).

197 Villages and road-network data are from The National Geographic & Hydrographic Institute of
198 Madagascar (www.ftm.mg), originally for 1964 and updated in 1990). These data are 1:500,000.
199 The 'Path Distance' tool was used to process these data in order to derive distances to Primary
200 and Secondary Roads. Population density comes from the 2000 Global Gridded Population
201 Database of the Center for International Earth Science Information Network (CIESIN).

202 **4. Results**

203 Protected Area Locations and Deforestation

204 In Table 2 we provide a naïve estimate of the impact of PAs on deforestation by showing rates of
205 deforestation for protected and unprotected locations, for PAs established prior to the year 2000.

206 For the higher 1990-2000 deforestation rates, comparing deforestation in PAs to deforestation in
207 all of the unprotected sites suggests a 7% reduction in deforestation due to those pre-1990 PAs.

208 The 2000-2005 deforestation rate is lower. Comparing the deforestation rates in the PAs to all of
209 the unprotected lands suggests about a 2% reduction in deforestation due to pre-1990 PAs. With
210 slightly lower internal clearing, the PAs created in 1990-1999 had a greater impact (over 2.5%).

211 We call such estimates of PA impact 'naïve' because they ignore the differences in characteristics
212 shown in Table 2 between the protected lands and unprotected lands on average in Madagascar.

213 For instance, the protected sites are further from roads and on average also are on steeper slopes.

214 That is consistent with results from Green *et al.* 1990 and Sussman *et al.* 1994, for Madagascar,

215 and Joppa & Pfaff 2009 globally. Table 3a's multivariate regression summarizes the differences

216 in sites by showing the effect of all our landscape characteristics on the probability of protection.

217 Drivers of Deforestation

218 The differences just documented, across protected and unprotected sites, matter for the rate of

219 deforestation. Table 3b's OLS regression for deforestation for only unprotected locations shows

220 this holds independent of any PA impacts. This shows important drivers of both 1990-2000 and

221 2000-2005 deforestation pressures. By implication, pressures varies greatly across the landscape

222 (per time periods, coefficients tend to be smaller in later period given less deforestation overall).

223 For example, roads cause pressure to vary in both time periods, though not surprisingly there are
224 shifts across time in where pressures are highest (Haruna et al. 2014 discuss the value, for policy,
225 from an ability to anticipate shifts in pressure, while demonstrating shifts in pressure in Panama).
226 For Madagascar, the secondary road network has consistent impacts but the pressure frontier is
227 farther from primary roads in our second time period of deforestation, i.e., during 2000-2005.
228 Slopes and provinces also have consistent effects – though again smaller in the second period.

229 Impacts of PAs – OLS Regression

230 As a first effort to control for differences in site characteristics in estimating PA impact, Table 3c
231 combines Table 3b's factors with PAs to explain deforestation in unprotected and protected sites
232 (we present OLS regressions for easy interpretation; Probit's marginal impacts are very similar).
233 Controlling for site differences does affect impact estimates relative to naïve. Not surprisingly to
234 control for the pre-1990 PAs' locations lowers the PA-impact estimate but it remains positive and
235 statistically significant, although of course lower for the second time period given lower clearing.
236 For 1990-2000 deforestation, the estimate of PA impact using controls is a bit more than 6% –
237 i.e., lower than Table 2 difference in the raw means yet clearly significantly different from zero.
238 For 2000-2005 deforestation, given lower pressure those same pre-1990 PAs avoid only ~ 1.4%
239 deforestation. Interestingly, however, for the new 1990-1999 PAs the 2000-2005 impact estimate
240 is ~ 2.5%, higher than for older PAs and, in fact, much like the difference in raw means. It could
241 be that actors were better able to anticipate future clearing pressures when creating the later PAs.

242 Impacts of PAs – Matching

243 Table 4 shows that matching protected points to the most observationally similar unprotected
244 ones clearly reduces the differences in characteristics between the protected and control points.

245 For instance, distances to roads and slope are significant factors in deforestation and both show
246 significant differences between protected and unprotected locations that Table 4 shows both fall
247 (this 'balance' table shows these reductions in difference as raw values and in standardized form).

248 Based on matched samples, Table 5 shows matching estimates for PA impacts on deforestation
249 within the pre-1990 PAs (for both 1990-2000 and 2000-2005 deforestation) and 1990-1999 PAs
250 (2000-2005 deforestation only). For the pre-1990 PAs, the additional (i.e., beyond OLS) control
251 for differences in characteristics lowers the estimated impacts coefficients for both time periods.
252 For the 1990-2000 deforestation, for instance, the estimate is on the order of 4% instead of 6%.
253 Interestingly, suggestive of different dynamics over time in political economy of PAs' locations,
254 for 2000-2005 deforestation matching correction raises (versus OLS) the estimate for later PAs.
255 Thus, vis-a-vis pressure, location processes seemed to operate quite differently for the later PAs.
256 Finally, addressing remaining differences in characteristics between the protected and matched
257 control points, OLS regressions using only the post-matching protected and unprotected samples
258 (also Table 5) support all of the conclusions derived from the standard matching impact analysis.

259 Varied PA Impacts Across The Landscape

260 Some subsets of PAs have reliably greater impact. From Pfaff et al. 2009 on Costa Rica, e.g., we
261 might often expect dependable variation in clearing pressure as a function of variation in drivers
262 and, thus, that well-enforced PAs vary in their impact (since without pressure there is no impact).
263 Thus, all else equal, if PAs were to be located on flatter lands and to be closer to roads and cities
264 while at least as well enforced – perhaps at a cost – then they could have higher forest impacts.
265 That is the clear prediction from almost any static land-use model (see Pfaff and Robalino 2012,
266 while Pfaff et al. 2013 and Pfaff et al. 2014 note that political economy modeling is needed too).

267 To demonstrate this for Madagascar, Table 6 presents variable 1990-2000 deforestation impacts
268 of the pre-1990 PAs, as a function of where those PAs are located on the landscape. Specifically,
269 Table 6 splits those pre-1990 PAs into subsets along three dimensions, or characteristics of sites
270 that often matter for deforestation pressure: distance to primary road; distance to secondary road;
271 and distance to urban area. Its two rows always split PAs into those with values: above the mean
272 calculated for the entire sample, for the indicated landscape characteristic; and below that mean.
273 The PAs closer to either type of road or the city have estimated impacts essentially twice as large
274 as for typically lower-pressure locations. Such sites might have higher financial or political costs.

275 Potential Impacts of Durban Vision Protected Areas

276 Viewing the recent expansion of Madagascar's PA portfolio through the lens of the deforestation
277 drivers and all the previous PA impacts is helpful for understanding how effectively Madagascar
278 has scaled up their conservation efforts through the Durban Vision. From Tables 2 and 3 above,
279 the characteristics of the sites of the newest PAs are associated with relatively high PA impacts.
280 For instance, each successive generation of PAs has lower slopes and the PAs created as part of
281 the Durban Vision are closer to each of the road types as are the averages for all of the prior PAs.

282 **5. Discussion**

283 For a country with important biodiversity, this analysis adds to a rapidly growing literature that
284 demonstrates the importance of checking whether outcomes in PAs imply *impacts* of protection.
285 For conservation organizations, and for other institutions with overlapping mandates for support,
286 if good data exist such impact evaluations can be done quickly and cheaply to provide guidance.

287 However, data with appropriate spatial coverage, and resolution, for the time period of interest,
288 will not always be immediately at hand. For instance, data for some potential driving factors in

289 deforestation were not found for dates before 1990. If those factors responded to siting of PAs,
290 that could bias our estimates of PA impacts. This motivates ongoing search for additional data –
291 at the least facilitating robustness tests suggested by the consideration of many such possibilities.

292 Additional data could also permit extensions, for instance comparing impact across types of PAs
293 or, with later deforestation data, evaluating not only the location but also the impact of new PAs.
294 Earlier deforestation data also can help to understand whether the pool of forest shifted over time
295 such that the currently standing forests, used as controls here, were those facing lower pressures.

296 Given those limitations, which we believe motivate attempts to extend what we have found here,
297 we found that protection lowered the 1990-2000-2005 deforestation rates within PA boundaries
298 in Madagascar, albeit by less than is estimated without matching methods' control for locations.
299 Impacts are lower during the second time period because there is less clearing for PAs to block.

300 Nearer to roads and cities, where there tends to be higher deforestation pressures on unprotected
301 lands, PA impacts are indeed higher, although the same pressures could raise costs at these sites.

302 Finally, the characteristics of the many new 2003-2008 PAs – created after the Durban Vision –
303 suggest at least an expansion of the significant PA impacts established by earlier Malagasy PAs.
304 Maintaining or increasing this will not be easy, especially if global markets focus on resources
305 found within Madagascar's PAs. For instance, the heightened demand for rosewood, as well the
306 illegal extraction from Madagascar's forests that followed (see discussion in Barrett *et al.* 2010)
307 highlights challenges for conserving Madagascar's biodiversity regardless of land characteristics.

308 Wherever sources of pressure exist, effective monitoring, legislation, and enforcement will be
309 required to capitalize on Madagascar's ongoing positive investment in lands worth conserving.

310

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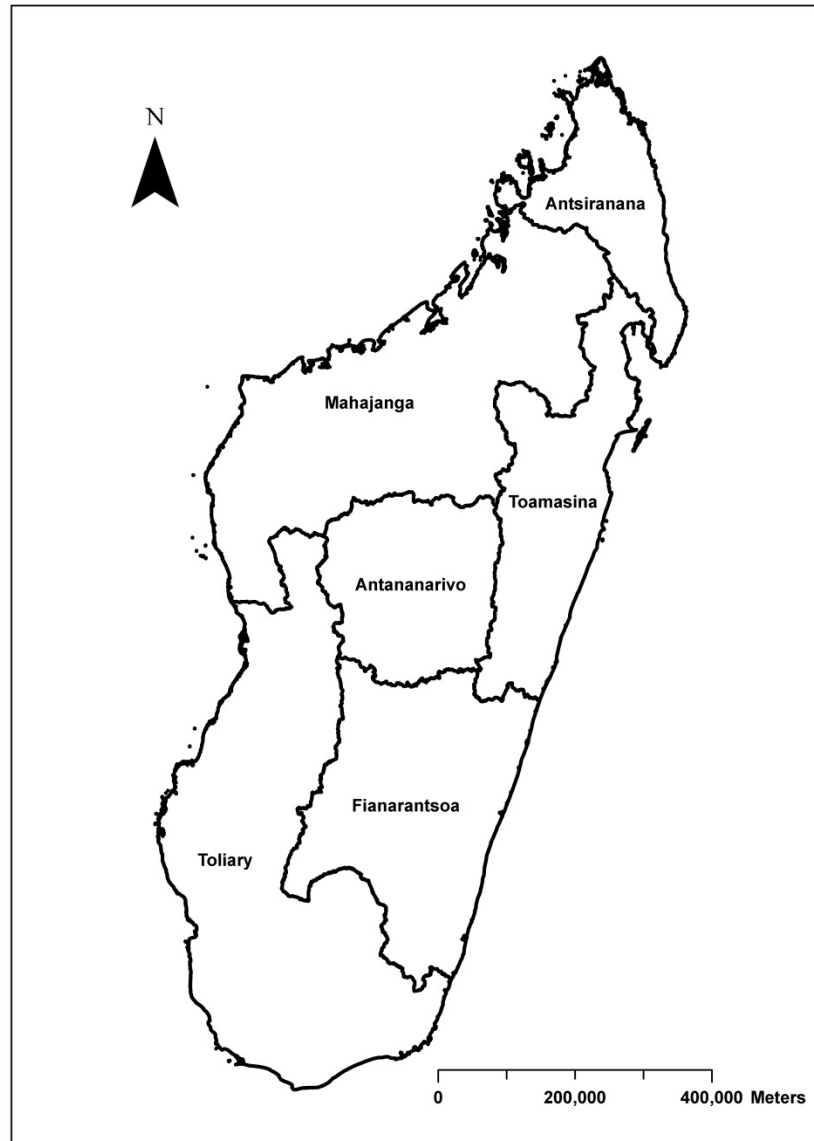
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Figure 1

Past Administrative Regions in Madagascar

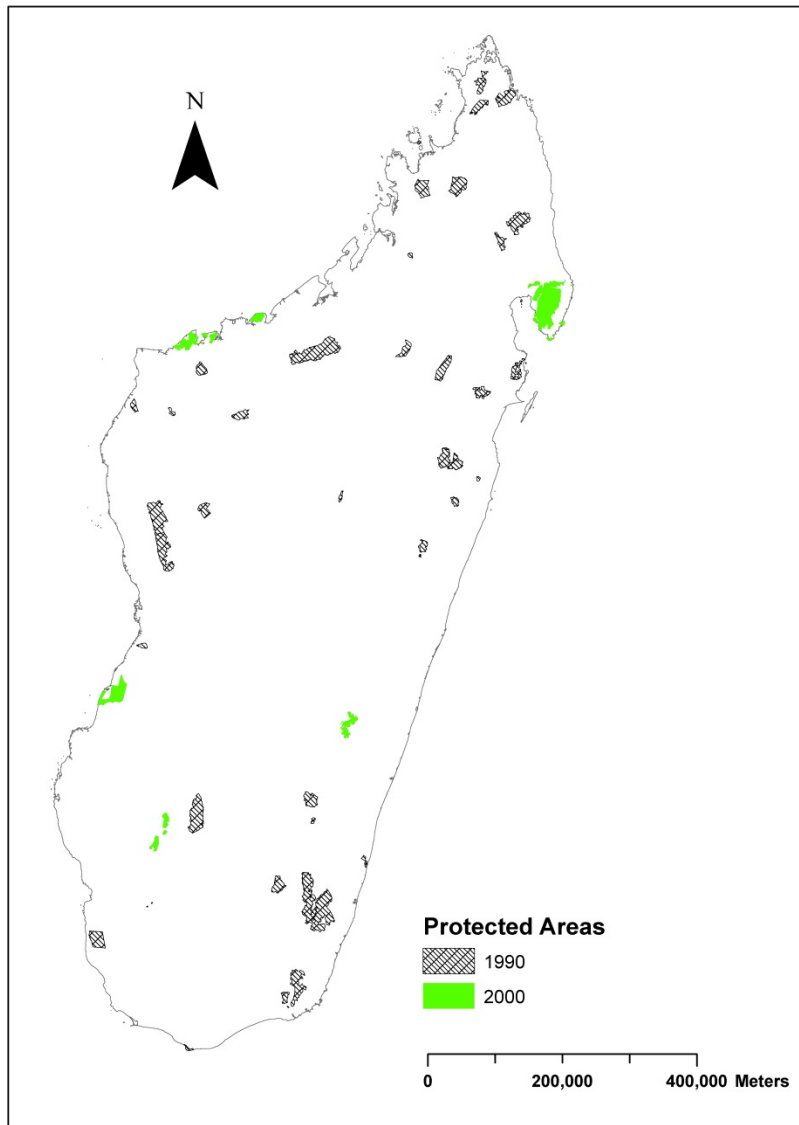


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Figure 2

Malagasy Protected Areas Established Before 2000



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