

<sup>1</sup> Using balanced acceptance sampling as a master  
<sup>2</sup> sample for environmental surveys

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## Abstract

Well designed environmental monitoring programmes for management organisations are important for evidence based decision making. However, many environmental problems are not single agency, single spatial scale issues. A master sample can be used to coordinate and scale monitoring designs to ensure consistency in information gathered and robustness of estimators at the different spatial scales. We propose using balanced acceptance sampling (BAS) to generate a master sample. Using Bas as a master sample is flexible, effective and improves on other methods previously explored. Some practical aspects of the design are addressed such as inclusion of legacy monitoring programmes, stratification, unequal probability sampling, rotating panel designs, and regional intensification. We explore the impact of including legacy monitoring through a simulation study. An example master sample is presented for environmental monitoring in New Zealand.

<sup>23</sup>      **Keywords:** Master Sample, Spatial Balance, Environmental Monitoring,  
<sup>24</sup>      Legacy Monitoring.

<sup>25</sup>

## 1 Introduction

<sup>26</sup>      Environmental management agencies rely on the results of monitoring to answer  
<sup>27</sup>      questions about the success of their policies and programmes. Monitoring is  
<sup>28</sup>      often designed to address informations needs for a particular site or small set  
<sup>29</sup>      of sites. The quality of monitoring designed for site specific needs can vary  
<sup>30</sup>      greatly. Poor monitoring design can result in failure to provide meaningful data  
<sup>31</sup>      to inform management and policy decision making (Legg & Nagy 2006; Nichols  
<sup>32</sup>      & Williams 2006; Field *et al.* 2007). Extrapolating from these studies to answer  
<sup>33</sup>      larger scale questions can introduce bias into the estimates as single sites are  
<sup>34</sup>      rarely representative of a broader region (Peterson *et al.* 1999; Dixon *et al.*  
<sup>35</sup>      1998).

<sup>36</sup>      Increasingly there is a need to monitor natural resources across broad spatial  
<sup>37</sup>      scales (ref). This is often undertaken by different agencies, which may or may  
<sup>38</sup>      not share the same purpose or objectives. This can to divergent approaches to  
<sup>39</sup>      monitoring even though the resource of interest is the same (Larsen *et al.* 2008).  
<sup>40</sup>      Coordinating monitoring requires consistent approaches to the formulation of  
<sup>41</sup>      goals and objectives, selection of indicators and measures, field protocols and  
<sup>42</sup>      sample design (Fancy *et al.* 2009; Larsen *et al.* 2008). Material exists to assist  
<sup>43</sup>      in creating a well designed monitoring programme (Gitzen 2012; Reynolds *et al.*

<sup>44</sup> 2016; Vos *et al.* 2000) but coordination is required to ensure it is carried out  
<sup>45</sup> properly and that standards are consistently applied. If one agency establishes  
<sup>46</sup> monitoring locations using standard methods and sample design, another agency  
<sup>47</sup> can use that data for their own purposes, reducing the need to establish more  
<sup>48</sup> monitoring. By agencies working together and through a well set out design  
<sup>49</sup> process the chances of monitoring being successful are higher. Concerns about  
<sup>50</sup> the extrapolating estimates from disparate data sources is also reduced.

<sup>51</sup> One way to coordinate sample design is to develop a master sample; a set of  
<sup>52</sup> points that can be sub-sampled for different monitoring activities. This was first  
<sup>53</sup> proposed by (King 1945), but only recently has been introduced to environmen-  
<sup>54</sup> tal monitoring (Larsen *et al.* 2008; Theobald 2016) with implementation in the  
<sup>55</sup> Pacific Northwest of the United States. Having different studies draw samples  
<sup>56</sup> from the master sample has the benefit of enhancing collaboration within and  
<sup>57</sup> between agencies to reduce duplication of effort. Additionally, consistent sam-  
<sup>58</sup> ple design has benefits when making estimates using data from multiple sources.  
<sup>59</sup> Similar to providing standard field methods, the master sample provides stan-  
<sup>60</sup> dardised locations for sampling that ensures objective, unbiased estimation of  
<sup>61</sup> the population parameters of interest. This coordination reduces convenience or  
<sup>62</sup> judgement sampling and requires the user to define the objectives and sample  
<sup>63</sup> frame clearly before gaining access to the sampling locations.

<sup>64</sup> The sampling method chosen should be flexible enough for a variety of users  
<sup>65</sup> and study designs to be effective for coordination. Monitoring can take place  
<sup>66</sup> on different spatial scales such as a national monitoring programme or a local

67 one, investigating the impact of management action. When designing an in-  
68 dividual study, identifying heterogeneity and using stratification (Yoccoz *et al.*  
69 2001) or unequal probability sampling (Stevens 1997) can produce more precise  
70 estimates. The study may need a unique balance of status and trend estimation  
71 which can be done by defining panels that have different revisit schema (Skalski  
72 1990; McDonald 2003; Stevens & Olsen 1999). In all these cases the sub-samples  
73 used must be unbiased and representative.

74 The New Zealand Department of Conservation (DOC) is the lead biodi-  
75 versity management agency in New Zealand. It is progressively implement-  
76 ing a coordinated monitoring and reporting system. Existing legacy monitor-  
77 ing include a national sample of Public Conservation Land (PCL) and various  
78 projects established to address specific local issues with diverse sample designs  
79 and methods employed. Development of the monitoring system has exposed the  
80 challenges in coordinating monitoring design to provide results meaningful at a  
81 local, regional and national scales. Increasingly partner environmental agencies  
82 (local government etc.) and central government expect cross-agency collabora-  
83 tion and coordination of systems and processes. Considerable effort has gone  
84 into a coordinated approach to selection of indicators and measures and field  
85 protocols Department of Conservation (2016). A master sample is one tool to  
86 have a coordinated approach to generation of sample designs.

87 There are many ways to generate effective samples which could be used to  
88 coordinate monitoring. A simple random sample is unbiased but is less effi-  
89 cient than spatially balanced designs in the presence of spatial autocorrelation

90 (Grafström & Lundström 2013). A design is spatially balanced if the sample  
91 is well-spread over the population — a sample with few clumps and voids. A  
92 systematic sample can be considered near perfect spatial balance but is less flex-  
93 ible to changes in sample size making it a poor choice. Spatially balanced sam-  
94 pling designs are commonly used for sampling natural resources and a variety  
95 of designs have been proposed. Stevens & Olsen (2004) introduced Generalized  
96 Random Tessellation Stratified (GRTS) design, a spatially balanced design that  
97 is frequently used in environmental monitoring. GRTS hierarchically orders a  
98 population using a base four numbering scheme and then selects a systematic  
99 sample from the ordered population. Another spatially balanced design is the  
100 Local Pivotal Method (LPM) (Grafström *et al.* 2012). LPM iteratively updates  
101 each sampling unit’s inclusion probability in a way that makes it very unlikely  
102 to include neighbouring units in a sample. Once  $n$  units have an inclusion prob-  
103 ability of one, the sample is released. Although the spatial balance of LPM is  
104 better than GRTS, it is computationally prohibitive on large populations. For  
105 large populations, Grafström *et al.* (2014) introduced a new rapid implemen-  
106 tation of LPM, called suboptimal LPM. LPM has better spatial balance, but  
107 suboptimal LPM is computationally feasible on large populations.

108 GRTS has been used to generate environmental monitoring master samples  
109 (Larsen *et al.* 2008). The design is particularly useful for generating master  
110 samples because GRTS points are ordered using a reverse hierarchical ordering  
111 strategy that ensures that all contiguous sub-samples are also spatially bal-  
112 anced (Stevens & Olsen 2004). By taking a large GRTS oversample, an ordered

113 master sample can be obtained from which spatially balanced sub-samples can  
114 be drawn. However, once an oversample is chosen, it is not possible to gen-  
115 erate additional points and this needs to be accounted for at the planning  
116 stage. Theobald (2016) also uses an adaptation of GRTS, Reversed Random-  
117 ized Quadrant-Recursive Raster (RRQRR), implemented in ArcGIS software  
118 (Theobald *et al.* 2007) to coordinate monitoring effort. The authors' are not  
119 aware of an ordering strategy for the LPM methods and hence, it is not clear  
120 how these methods could be used for oversampling. Another spatially balanced  
121 design is balanced acceptance sampling (BAS) (Robertson *et al.* 2013). It uses  
122 a quasi-random number sequence to generate spatially balanced points. Similar  
123 to GRTS, the outcome of the sequence is an ordered set of points such that any  
124 contiguous sub-sample maintains spatial balance. To generate a master sample  
125 with BAS, a random-start is chosen and after that an infinite set of points exist  
126 for the sample. Hence, the oversample size does not need to be specified for  
127 BAS.

128 This paper describes the development of a master sample for environmen-  
129 tal monitoring in New Zealand, with a focus on terrestrial sampling of an area  
130 frame in which all sub-samples have positive area. We investigate using BAS  
131 to generate a master sample; how the points will be generated and then used  
132 in a for a range of applications. These include adapting to different spatial  
133 scales, stratification and unequal probability sampling, changes in boundaries  
134 or resources, revisit structure (panel design), and inclusion of legacy mon-  
135 itoring. We will then provide an example for how this could be applied at the

<sup>136</sup> regional and national level in New Zealand.

## <sup>137</sup> 2 Methods

### <sup>138</sup> 2.1 Point selection

Two-dimensional BAS points are drawn from a random-start Halton sequence  $\{\mathbf{x}_k\}_{k=1}^{\infty} \subset [0,1]^2$ . The  $i$ th coordinate of each point in the sequence has an associated base  $b_i$ , with  $b_1 = 2$  and  $b_2 = 3$ . The  $i$ th coordinate of the  $k$ th point in this sequence is (Robertson et al. 2017)

$$x_k^{(i)} = \sum_{j=0}^{\infty} \left\{ \left\lfloor \frac{u_i + k}{b_i^j} \right\rfloor \bmod b_i \right\} \frac{1}{b_i^{j+1}},$$

<sup>139</sup> where  $u_i$  is a random non-negative integer and  $\lfloor x \rfloor$  is the floor function — the  
<sup>140</sup> largest integer that is less than or equal to  $x$ . The two-dimensional random-start  
<sup>141</sup> Halton sequence is

$$\{\mathbf{x}_k\}_{k=1}^{\infty} = \left\{ x_k^{(1)}, x_k^{(2)} \right\}_{k=1}^{\infty}. \quad (1)$$

<sup>142</sup> Setting  $u_1 = u_2 = 0$  gives the classical Halton sequence (Halton 1960). The  
<sup>143</sup> points from eqn (1) are scaled to a minimal bounding box enclosing the study  
<sup>144</sup> area and the first  $n$  scaled points in the study area define the BAS sample. The  
<sup>145</sup> BAS points are kept in the same order as they appear in eqn (1) and will have  
<sup>146</sup> good spatial spread over the study area. Furthermore, any continuous subset  
<sup>147</sup> of the BAS sample will also have good spatial spread (Robertson et al. 2017).

<sup>148</sup> Figure 1 shows an example of how this sequence creates spread by systematically  
<sup>149</sup> choosing between boxes generated by the choice of the co-prime bases.

150        The random integer vector in the sequence  $\mathbf{u} = (u_1, u_2) \in [0, 10^7]^2$  is chosen  
151        so that  $\mathbf{x}_1$  falls within the sample area (Robertson *et al.* 2017). This gives  
152         $O(\lambda 10^{14})$  possible BAS samples of size  $n$ , where  $\lambda$  is the fraction of the bounding  
153        box occupied by the study area. By ensuring the random start comes from a  
154        large set of integers, the BAS points are uniformly distributed (Robertson *et al.*  
155        2013). Once the random-start is selected an infinite number of BAS points exist  
156        over the study which constitutes the master sample. Higher dimensional points  
157        can be defined by using different co-prime bases for each additional dimension  
158        (e.g.  $b_3 = 5$  when sampling from a  $[0, 1]^3$ ).

## 159        2.2 Spatial Scales

160        The Master sample should work at different spatial scales to answer national,  
161        regional, and local objectives. Let  $A$  be a measurable subset of the study area  
162        for which the master sample is defined. Because the master sample  $\{\mathbf{x}_k\}_{k=1}^\infty$   
163        is uniformly distributed over  $[0, 1]^2$  (Wang & Hickernell 2000), there exists a  
164        subsequence  $\{\mathbf{z}_j\}_{j=1}^\infty \subset \{\mathbf{x}_k\}_{k=1}^\infty$  such that each  $\mathbf{z}_j \in A$ . Furthermore,  $\{\mathbf{z}_j\}_{j=1}^n$   
165        is a BAS sample of size  $n$  drawn from  $A$ , with its random start and bounding  
166        box defined by the master sample. Hence, BAS samples can be drawn from the  
167        master sample at any spatial scale within the study area of the master sample.

168        What this means is that a national sample can share locations with moni-  
169        toring at the local level. Let's say that nationally 1000 sites are generated, each  
170        with a unique order. If a sample of a region is taken and by chance 10 of these  
171        sites are shared, then the first ten sites in the regional sample are monitored by

172 the national programme.

### 173 2.3 Stratification and Unequal probability

174 Stratification with the master sample is essentially the same as taking a sub-  
175 sample for a specific measurable subset of the study area as described above.

176 The  $i$ th stratum (measurable) has a subsequence  $\{\mathbf{z}_j\}_{j=1}^{\infty} \subset \{\mathbf{x}_k\}_{k=1}^{\infty}$  such that  
177 each  $\mathbf{z}_j$  is in the stratum. The BAS sample for the  $i$ th stratum is  $\{\mathbf{z}_j\}_{j=1}^{n_i}$ ,  
178 where  $n_i$  is the sample size required. Hence, each stratum has its own BAS  
179 sample with its random start and bounding box defined by the master sample.

180 In practice, each strata has the number of points required by taking a subset of  
181 the master sample for that strata.

182 If unequal probability sampling is required, a third dimension is added to the  
183 bounding box. This extra dimension allows BAS to sample from an arbitrary  
184 inclusion density function  $\pi(\mathbf{x})$  using an acceptance/rejection sampling strategy  
185 (Robertson *et al.* 2013). Specifically, a point  $\mathbf{x}_k = (x_k^{(1)}, x_k^{(2)}, x_k^{(3)})$  is accepted  
186 if  $(x_k^{(1)}, x_k^{(2)})$  is in the study area and  $\pi(x_k^{(1)}, x_k^{(2)}) \leq \alpha x_k^{(3)}$ , where  $\alpha$  is a scaling  
187 factor to ensure  $\max_{\mathbf{x}} \pi(\mathbf{x}) = 1$ . The impact of this is that some of the master  
188 sample points in eqn (1) will be skipped. This changes the density of BAS points,  
189 where fewer points are drawn from areas where  $\pi(\mathbf{x})$  is low. The resulting sample  
190 will still maintain order of the master sample but be missing points that were  
191 rejected due to unequal probability sampling.

192 **2.4 Changing boundaries and resources**

193 For long-term monitoring programmes, the boundaries of study regions may  
194 change over time. This is easy to accommodate with the master sample, pro-  
195 vided the changes are within the initial bounding box. Let  $A$  be a measurable  
196 study area whose boundaries changed, defining a new measurable study area  $B$   
197 with  $A \cap B \neq \emptyset$ . If there are no sampled BAS points in  $A \cap B$ , points from the  
198 master sample are drawn to sample  $B$ . Otherwise, let  $\mathbf{x}_k$  be the sampled point  
199 in  $A \cap B$  with the largest index  $k$ . A BAS sample in  $B$ , that includes sampled  
200 points from  $A \cap B$ , is achieved if all master sample points that fall in  $B$  with  
201 indices less than  $k$  are sampled. If a smaller sample is desired in  $B$ , potentially  
202 due to a change in resources, then points with the larger indices in  $B$  are re-  
203 moved. In the same sense if more points are required then points can be added  
204 from the master sample in  $B$  until the new sample size is achieved. Ensuring  
205 that BAS samples are drawn from each study region means that spatial balance  
206 and good sampling properties are maintained. This is demonstrated in Figure  
207 2, where the region is expanded but resources are not. The highest index points  
208 from  $A \cap B$  are dropped for new points in  $\bar{A} \cap B$ , the additional region.

209 **2.5 Panel design**

210 In environmental surveys that are repeated through time some samples may be  
211 visited frequently and others potentially once. This can allow better estimation  
212 of status when only new samples are included during each session or trend where  
213 the same samples are visited more frequently (Urquhart & Kincaid 1999). A

214 panel is defined as all samples that have the same visitation schedule. The  
215 points within a panel as well as between panels must be representative and  
216 unbiased. A panel design is achieved using the master sample by choosing the  
217 subset of points  $\{\mathbf{z}_j\}_{j=1}^{\infty}$  that fall within the sample frame and then selecting in  
218 order points for each panel matched to how they will be sampled in time. Thus,  
219 for panel 1 with 10 points we have the sample  $\{\mathbf{z}_j\}_{j=1}^{10}$  and panel 2 with an  
220 additional 10 is  $\{\mathbf{z}_j\}_{j=11}^{20}$ . When establishing the sample each year, some points  
221 within the panel may not be able to be sampled. If this occurs, then those  
222 locations are not truly part of the sample frame and are removed from  $\{\mathbf{z}_j\}_{j=1}^{\infty}$ .  
223 In the example above, if a single point is removed from panel 1, then  $\{\mathbf{z}_{11}\}$   
224 is now actually  $\{\mathbf{z}_{10}\}$  and replaces the missing point in panel 1. By defining  
225 the panels this way the overall sample is still a BAS design as well each panel.  
226 Once a full rotation of all samples has been carried out, if additional points  
227 are needed, they are added from the unsampled points in the master sample  
228 in the order that they appear. Note, when this occurs each panel may not be  
229 a true BAS sample but as shown in the legacy plots simulation below, adding  
230 BAS points to an existing sample does not significantly impact estimation and  
231 the sample will still be equi-probable and give unbiased estimators. If budgets  
232 change, points should be removed by last in, first out. Table 1 shows an example  
233 panel design.

234 **2.6 Incorporating legacy monitoring**

235 A master sample is intended for coordinating large scale monitoring. Often,  
236 there is legacy monitoring that may already be well designed and this should  
237 be accommodated. We will consider two different types of monitoring: sim-  
238 ple random sampling (SRS) and random-start systematic sampling (SS). These  
239 monitoring approaches are equi-probable designs, where each sampling unit has  
240 an equal chance of being included in a sample, but differ in extremes of spatial  
241 balance. If the existing monitoring is insufficient then the master sample must  
242 be able to augment sampling in the area. BAS points can intensify the legacy  
243 points by generating them independently. For unbiased estimation inclusion  
244 probabilities need to be computed. For a population of  $N$  units, the inclusion  
245 probability of the  $i$ th unit is assumed to be  $\pi_i = (n_l + n_b)/N$  because both  
246 sets of units were selected using equal probable designs, where  $n_l$  and  $n_b$  denote  
247 the number of legacy and BAS units respectively. The approach keeps the de-  
248 sign and analysis simple but potentially loses the appearance of spatial balance.  
249 Another method is to alter the inclusion probabilities around the legacy plots  
250 before sampling to ensure that none of the augmented samples are close to the  
251 legacy plots but this is at the expense of complexity of design and analysis as  
252 shown in (Foster *et al.* 2017). If this approach is desired a BAS master sample  
253 can accommodate the change in inclusion probabilities which is described above.  
254 We will call the altered inclusion probability sample aBAS from here on out.

255 A simulation study was carried out to investigate the impact of choosing  
256 different methods to incorporate legacy monitoring. The sampling frame was

257 defined as  $100 \times 100$  raster in  $[0, 1]^2$ . The response value for each raster cell  
258 was defined as the integral of  $f(\mathbf{x})$  over the cell. Three different functions were  
259 estimated, a strong spatial trend (Robertson *et al.* 2013; Grafström *et al.* 2012),  
260 a peak function, and a bird (cyclical trend) function. Scenarios similar to Foster  
261 *et al.* 2017 using the program R (R Core Team 2015) were run. We assumed  
262 an arbitrary overall sample size of  $n = 60$ . Legacy plots ( $n_l \in 3, 4, \dots, 57$ ) were  
263 generated either as simple random samples (SRS) or random-start systematic  
264 samples (SS). More samples ( $n_b = 60 - n_l$ ) were then included using GRTS  
265 (Kincaid & Olsen 2016), BAS, and aBAS (Foster 2016). SRS were added to  
266 SS legacy plots as well. Each scenario was run 1000 times estimating the sam-  
267 ple mean. A detailed description of the simulation and functions used can be  
268 accessed in the supplementary material.

269 Balanced acceptance sampling generally has better spatial balance than  
270 GRTS (Robertson *et al.* 2013), aBAS has the appearance of better spatial bal-  
271 ance as the proportion of legacy plots increases when they are simple random  
272 samples (Foster *et al.* 2017). The results of the simulation can be seen in Figure  
273 3 and Tables 2 & 3. Based on these simulations, augmenting legacy monitoring  
274 with BAS or GRTS is reasonable. Altering inclusion probabilities does not seem  
275 necessary for augmenting a legacy sample. In fact, there are cases when this can  
276 be dangerous as seen by the aBAS spikes (high standard deviation) in Figure 3.  
277 This is because the legacy monitoring may happen to coincide with a particular  
278 trend in the population and forcing monitoring away from the legacy plots can  
279 be problematic. Spatially balanced unequal probability sampling is only use-

ful (i.e. reduces the variance of an estimator) if the inclusion probabilities are positively correlated with the response. We suggest that unequal probability sampling be only undertaken in response to information about the population being monitored and not legacy plots. However, there are practical constraints on sampling that might make it unpopular for monitoring sites to fall directly next to each other, which is possible in the described approach. This makes aBAS attractive in the field but we recommend using model based estimation and not design to control for the increased uncertainty using the method.

Estimation when including legacy plots is straightforward assuming the legacy monitoring has known inclusion probabilities. However, spatially balanced designs use a local neighbourhood variance (LNV) (Stevens & Olsen 2003) and as the proportion of legacy plots is increased the LNV underestimates true variance (Foster *et al.* 2017). If the legacy plots and the augmented sampling are considered two groups with sample size  $n_l$  and  $n_b$  ( $n_l + n_b = n$ ) respectively, then a weighted variance estimator for the sample mean  $\bar{y}$  would be

$$\hat{var}(\bar{y}) = \frac{n_l}{n} \times \hat{var}(\bar{y}_l) + \frac{n_b}{n} \times \hat{var}(\bar{y}_b). \quad (2)$$

Here  $\hat{var}(\bar{y}_l)$  is the estimated variance of a Horvitz-Thompson mean using the legacy points and  $var(\bar{y}_b)$  is the LNV estimated variance of the mean using BAS points. This corrects the underestimation of LNV and should be used any time there are four or more spatially balanced points as suggested in the spsurvey package in R (Kincaid & Olsen 2016) and three or more legacy points. Note that the weighted mean estimate remains unchanged as a result of equal

<sup>301</sup> probability sampling using either BAS or GRTS to augment legacy monitoring.

### <sup>302</sup> 3 Application: New Zealand terrestrial moni- <sup>303</sup> toring

<sup>304</sup> There currently exists a national monitoring programme in New Zealand ad-  
<sup>305</sup> ministered jointly by the Ministry for the Environment (MFE) and Department  
<sup>306</sup> of Conservation (DOC) for the purpose of carbon monitoring on an 8 km sys-  
<sup>307</sup> tematic grid (Coomes *et al.* 2002). The Department of Conservation added  
<sup>308</sup> monitoring of birds, mammals and vegetation at  $\approx$  1400 locations falling within  
<sup>309</sup> public conservation land (PCL) with a  $[(1 - 4)^5]$  revisit scheme where a single  
<sup>310</sup> panel is measured each year (Tier 1 monitoring). The programme focusses on  
<sup>311</sup> status and long term trend monitoring at the national scale. It is not able to  
<sup>312</sup> provide evidence of the success of management at a local scale or in response  
<sup>313</sup> to a particular action. However, for large parks (e.g. Fiordland National Park)  
<sup>314</sup> Tier 1 can provide estimates of park or region level ecological integrity.

<sup>315</sup> Ecosystems across the PCL have been identified as high priority and are la-  
<sup>316</sup> belled Ecosystem Management Units (EMUs) in response to intermediate out-  
<sup>317</sup> come objective (IOO) 1.1 – “A full range of New Zealand’s ecosystems is con-  
<sup>318</sup> served to a healthy functioning state” (Department of Conservation 2013). These  
<sup>319</sup> areas are of special interest and have a high level of investment through man-  
<sup>320</sup> agement activity. To assess the management outcomes of IOO 1.1 and report  
<sup>321</sup> on success or adapt management for improvement, Tier 1 monitoring must be

~~322 augmented within the EMU sites. For this purpose DOC requires a national  
323 sample that incorporates the already existing systematic Tier 1 sample.~~

~~324 The New Zealand Department of Conservation (DOC) is the lead biodi-  
325 versity management agency in New Zealand. It is progressively implementing  
326 a coordinated monitoring and reporting system. Existing legacy monitoring in-  
327 clude a national sample of Public Conservation Land (PCL) and various projects  
328 established to address specific local issues with diverse sample designs and meth-  
329 ods employed. Development of the monitoring system has exposed the challenges  
330 in coordinating monitoring design to provide results meaningful at a local, re-  
331 gional and national scales. Increasingly partner environmental agencies (local  
332 government etc.) and central government expect cross-agency collaboration and  
333 coordination of systems and processes. Considerable effort has gone into a co-  
334 ordinated approach to selection of indicators and measures and field protocols  
335 Department of Conservation (2016). A master sample is one tool to have a  
336 coordinated approach to generation of sample designs.~~

~~337 DOC manages c.30% of New Zealand as PCL. The national sample of PCL,  
338 known as the National Level Monitoring (NLM) programme is a centrally co-  
339 ordinated programme monitoring c.1400 monitoring locations. Ongoing collab-  
340 oration with local government agencies has seen the same methods and sample  
341 design implemented off PCL. Other monitoring includes site or catchment level  
342 monitoring programmes focussed on assessing management outcomes at the lo-  
343 cal level.~~

~~344 A national sample of New Zealand using BAS can make up the master~~

345 sample, with the existing Tier 1 points included. For efficiency each island  
346 (North Island, South Island, Stewart Island, Chatham Islands, etc.) will be  
347 stratified and have their own bounding box and random seed. The seed chosen  
348 for the South Island was  $\mathbf{u} = (4887260, 18041662)$  with minimum bounding box  
349 in NZTM

$$[1089354, 1721164] \times [4747979, 5516919].$$

350 These values define the scaling needed to map the random start Halton points  
351 to the South Island of New Zealand (NZ). For example, the first point is

$$\begin{aligned}\mathbf{x}_1 &= (631810x_1^{(1)} + 1089354, 768940x_1^{(2)} + 4747979) \\ &\approx (1235673, 5075613).\end{aligned}$$

352 To sample EMUs in NZ using the master sample, select all sites that fall  
353 within EMU polygons. The actual required sample size, and what is measured  
354 should reflect the monitoring objectives and follow a similar process as outlined  
355 by (Reynolds *et al.* 2016). See Figure 4 for an example of clipping the master  
356 sample on the South Island into the first 500 samples that fall within EMUs.

357 The NEXT Foundation currently manages biodiversity at Abel Tasman Na-  
358 tional Park (ATNP), one of DOC's EMUs, in a partnership with DOC. Based  
359 on their agreement, the Tomorrow Accord, the NEXT Foundation is managing  
360 ATNP while ecological integrity is in a transitional phase. DOC will take over  
361 management activity once the park is in a maintenance phase. Monitoring needs  
362 to be undertaken to establish the current state of ATNP and then to determine

363 when ecological integrity has been restored. One of the indicators of ecological  
364 integrity was focussed on bird abundance and distribution through the park.  
365 A sample size of  $n_{total} = 65$  was chosen based on a precision analysis using  
366 simr (Green & MacLeod 2016) and historical bird count data from the Eglinton  
367 Valley. Temporal variation was expected to be less than spatial, therefore 15  
368 samples were selected to be measured annually, and the other 50 on a rotating  
369 5-year panel  $[1 - 0, (1 - 4)^5]$ . From the Tier 1 programme mentioned above,  
370 there were four legacy samples in the sample frame. If DOC implemented an  
371 EMU monitoring programme that had 500 augmented sites on the South Island,  
372 then there would be an additional seven points that were already monitored and  
373 funded by DOC using the master sample. These points are included in the ro-  
374 tating panel on years corresponding to the years they are to be sampled. See  
375 Figure 5 for an example of the selected points in this monitoring programme.  
376 Abel Tasman National Park is an example of localised monitoring using the  
377 master sample that can contribute to national estimates of bird abundance and  
378 distribution. DOC gets better precision with the increased sampling in ATNP  
379 and the NEXT Foundation saves resources by using DOC's national investment  
380 in monitoring explicitly in their design.

381 The master sample above is entirely defined by the seed **u** and the bounding  
382 box. Hence, there is no need for a repository to hold the coordinates. Compu-  
383 tationally the master sample is easy to run on the fly. Generating 65 points for  
384 Abel Tasman National Park in Figure 5 takes  $\approx 0.5$  seconds on a desktop com-  
385 puter. See supplementary materials for R script to generate a master sample in

386 New Zealand.

## 387 4 Discussion

388 A master sample can be a useful tool to organise environmental monitoring  
389 at different spatial scales as previously done using GRTS or RRQRR (Larsen  
390 *et al.* 2008; Theobald 2016). By using BAS instead of GRTS there is better  
391 spatial balance (Robertson *et al.* 2013) and no need for an oversample. It is also  
392 possible to add an extra dimension to do unequal probability sampling leading  
393 to an overall more flexible design. Depending on the population being sampled,  
394 spatial balance may or may not lead to a more precise sample than simple  
395 random sampling. However, it is likely that some spatial balance will improve  
396 efficiency for most designs. Not needing to oversample to create a master sample  
397 using BAS means that it will remain relevant at any scale that monitoring takes  
398 place no matter how localised. If an extra dimension is needed, for instance  
399 to take a proportional to surface area sample across mountainous regions with  
400 steep surfaces, the master sample can be adapted to incorporate this. Another  
401 benefit of BAS as a master sample is that it is computationally fast and easy  
402 to program. This reduces the effort needed for storing a million or more points  
403 on a file for others to use. Instead a user can run a provided R script loading  
404 their region as a shape file and generate their sample quickly and locally with  
405 unique IDs provided to keep track of sampling.

406 In our experience, any large scale long-term monitoring will need to incor-

<sup>407</sup> porate already existing monitoring programmes that are proven effective. This  
<sup>408</sup> was a requirement in developing a master sample for New Zealand. We have  
<sup>409</sup> shown that there is no major issue with incorporating legacy monitoring into the  
<sup>410</sup> design but recommend that all sites are rigorously vetted to ensure no known  
<sup>411</sup> biases are included if historically the sites were judgement samples or for other  
<sup>412</sup> reasons. Using panel designs can help incorporate the already existing visitation  
<sup>413</sup> schedule of the legacy plots into an efficient monitoring design. We also recom-  
<sup>414</sup> mend against incorporating legacy plots by selecting them if the BAS sample is  
<sup>415</sup> nearby, based on some criteria.

<sup>416</sup> The master sample helps coordinate the locations sampled for environmental  
<sup>417</sup> surveys. Every survey at the local and national level should still go through  
<sup>418</sup> rigorous design. This means defining the objectives of monitoring clearly and  
<sup>419</sup> the methods to use so that they are consistent with standard methodology as  
<sup>420</sup> required by the objective. By following the steps outlined in Reynolds *et al.*  
<sup>421</sup> (2016) and using the master sample for point generation we believe that the  
<sup>422</sup> monitoring programmes undertaken at all levels will have improved efficiency  
<sup>423</sup> and contribute to the overall knowledge of the population of interest.

## <sup>424</sup> 5 Acknowledgements

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## 520 **6 Supporting Information**

521 More information about the simulation study and the R code used to generate  
522 the Master Sample for New Zealand can be found in the supplementary text.

## 523 **7 Data Availability**

524 We present a maintained version of the R code to generate a master sample  
525 in New Zealand, including a shape file example on github for access to readers  
526 familiar with R. <https://github.com/ogansell/MSampNZ>.

527 **8 Author Contribution**

528 All authors had significant contributions to this research. The paper was ini-  
529 tiated by a requirement from the Department of Conservation for coordinated  
530 monitoring of ecosystems at the national level. This work fell directly to Ollie  
531 Gansel and Paul van Dam-Bates and Blair Robertson collaborated. We were  
532 funded as salary through our job roles at DOC and the University of Canterbury.

<sub>533</sub> **Figures and Tables**

Table 1: Example of a panel design in which panel 1 is sampled annually and panels 2-4 are sampled with a 2 year break in between described as  $[1-0, (1-2)^3]$  in McDonald (2003). The sample size (n) and the points from the master sample are shown along with an X indicating that the panel is sampled on that occasion.  $\{\mathbf{z}\}_j$  is the master sample set that falls within this sample frame.

Panel	n	Sample	Sample Occasion									
			1	2	3	4	5	6	7	8	9	10
1	20	$\{\mathbf{z}\}_{j=1}^{20}$	X	X	X	X	X	X	X	X	X	X
2	10	$\{\mathbf{z}\}_{j=21}^{30}$	X			X			X			X
3	10	$\{\mathbf{z}\}_{j=31}^{40}$		X			X			X		
4	10	$\{\mathbf{z}\}_{j=41}^{50}$			X			X			X	

Table 2: Results from the simulation study testing the impact of adding new samples from altered balanced acceptance sampling (aBAS), balanced acceptance sampling (BAS) and generalised random tessellation stratified (GRTS) to existing simple random samples (SRS). The mean and (standard deviation) is presented. Three populations with varying spatial structure were tested. Population 1, a strong spatial trend. Population 2, a peak function. Population 3, a cyclical (bird) function. The proportion of legacy plots is out of  $n = 60$  for each population.

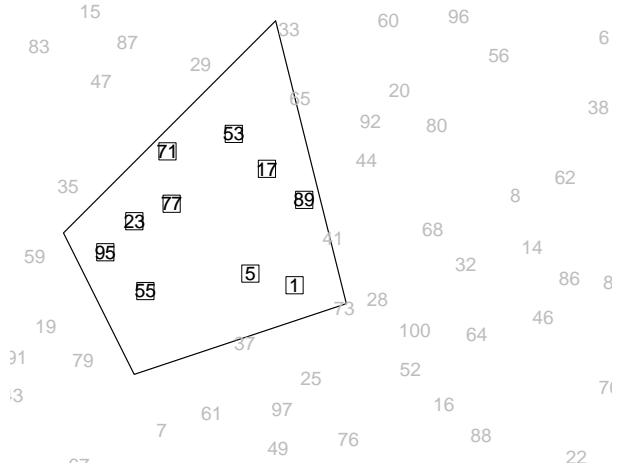
Population	Legacy	BAS	GRTS	aBAS
1	0.08	0.30 (0.008)	0.30 (0.009)	0.30 (0.043)
1	0.17	0.30 (0.009)	0.30 (0.010)	0.30 (0.021)
1	0.50	0.30 (0.014)	0.30 (0.015)	0.30 (0.036)
1	0.83	0.30 (0.018)	0.30 (0.018)	0.30 (0.030)
1	0.92	0.30 (0.018)	0.30 (0.018)	0.30 (0.026)
2	0.08	37.00 (15.9)	36.00 (14.5)	37.3 (19.3)
2	0.17	36.60 (15.1)	36.20 (16.7)	36.9 (19.7)
2	0.50	38.10 (20.7)	37.50 (21.2)	38.3 (29.5)
2	0.83	36.70 (25.5)	37.10 (25.2)	36.9 (26.9)
2	0.92	36.70 (24.2)	37.40 (23.6)	37.2 (25.7)
3	0.08	2.33 (0.29)	2.31 (0.30)	2.33 (0.39)
3	0.17	2.34 (0.32)	2.34 (0.34)	2.34 (0.42)
3	0.50	2.33 (0.40)	2.35 (0.43)	2.35 (0.69)
3	0.83	2.35 (0.50)	2.36 (0.48)	2.36 (0.62)
3	0.92	2.33 (0.48)	272.36 (0.49)	2.34 (0.51)

Table 3: Results from the simulation study testing the impact of adding new samples from altered balanced acceptance sampling (aBAS), balanced acceptance sampling (BAS), generalised random tessellation stratified (GRTS), and simple random sampling (SRS) to existing systematic samples (SS). The mean and (standard deviation) is presented. Three populations with varying spatial structure were tested. Population 1, a strong spatial trend. Population 2, a peak function. Population 3, a cyclical (bird) function. The proportion of legacy plots is out of  $n = 60$  for each population.

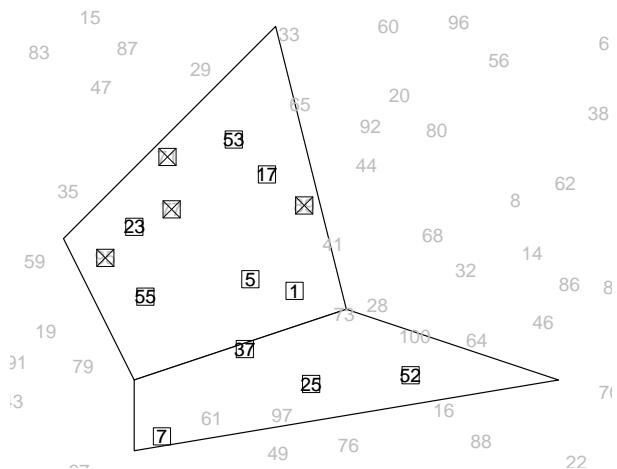
Population	Legacy	BAS	GRTS	SRS	aBAS
1	0.07	0.30 (0.006)	0.30 (0.007)	0.30 (0.018)	0.30 (0.017)
1	0.20	0.30 (0.006)	0.30 (0.008)	0.30 (0.017)	0.30 (0.033)
1	0.50	0.30 (0.007)	0.30 (0.009)	0.30 (0.014)	0.30 (0.027)
1	0.70	0.30 (0.008)	0.30 (0.010)	0.30 (0.013)	0.30 (0.020)
1	0.82	0.30 (0.012)	0.30 (0.013)	0.30 (0.014)	0.30 (0.018)
2	0.07	36.4 (15.0)	36.0 (13.6)	36.6 (24.1)	36.2 (17.8)
2	0.20	36.7 (12.0)	36.2 (14.0)	36.4 (22.7)	37.2 (18.2)
2	0.50	36.9 (12.0)	36.2 (12.2)	37.0 (17.5)	36.2 (40.2)
2	0.70	36.4 (11.0)	35.9 (10.5)	35.4 (13.8)	36.6 (16.8)
2	0.82	35.6 (11.0)	36.0 (9.2)	36.10 (10.7)	35.3 (12.0)
3	0.07	2.32 (0.32)	2.29 (0.31)	2.31 (0.51)	2.32 (0.44)
3	0.20	2.32 (0.26)	2.33 (0.29)	2.31 (0.46)	2.31 (0.43)
3	0.50	2.32 (0.24)	2.35 (0.28)	2.32 (0.37)	2.32 (0.40)
3	0.70	2.34 (0.26)	2.34 (0.27)	2.33 (0.32)	2.34 (0.34)
3	0.82	2.38 (0.27)	282.40 (0.28)	2.38 (0.31)	2.38 (0.35)

C	F
E	B
A	D

Figure 1: A Halton grid with (2,3) co-prime base. The order of points are alphabetical. If the first sample lands in B, the next five would land in (C, D, E, F, A). This structure repeats itself including within each rectangle.



(a)



(b)

Figure 2: Example of changing boundaries using the master sample showing some of the first 100 points in  $[0,1]$ , the order of which is shown by the numbers. A sample of 10 is then selected in the original study (a). In (b), an area is added to the study region but resources still only allow 10 samples. Points 71, 77, 89 and 95 are removed and replaced by 7, 25, 37 and 52 in the new region.

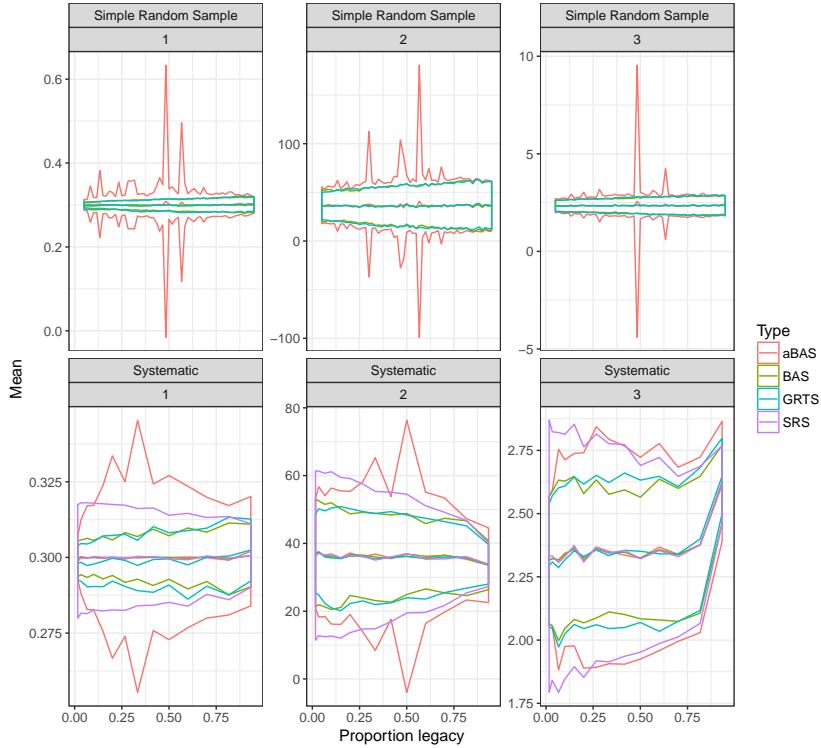
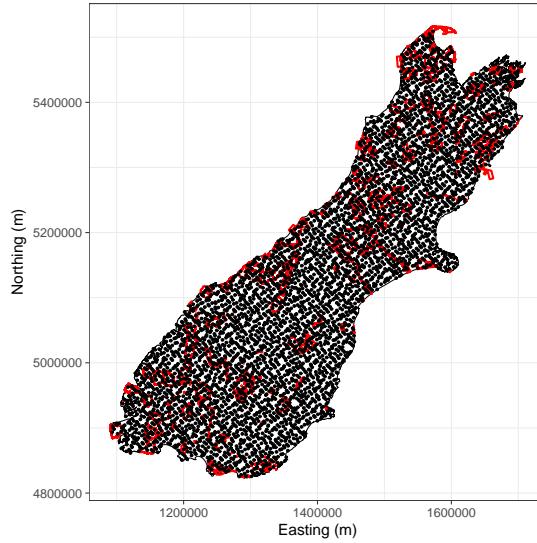
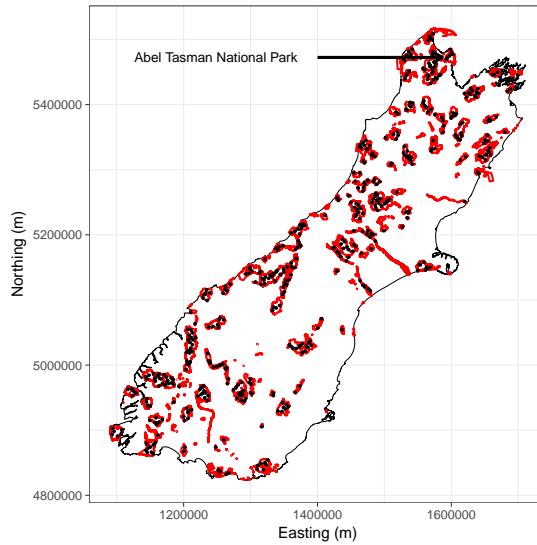


Figure 3: Results from the simulation study testing the impact of adding new samples from altered balanced acceptance sampling (aBAS), balanced acceptance sampling (BAS), generalised random tessellation stratified (GRTS), and simple random sampling (SRS) to existing legacy monitoring locations. Three populations with varying spatial structure were tested. Population 1, a strong spatial trend. Population 2, a peak function. Population 3, a cyclical (bird) function.



(a)



(b)

Figure 4: South Island of New Zealand (a) shows the first 5000 points of the master sample overlayed on red ecosystem management units (EMUs). (b) shows a sample size of 500 of master sample points from (a) that fall within the EMUs in red. Abel Tasman National Park receives seven samples which are included as the first seven in Figure 5

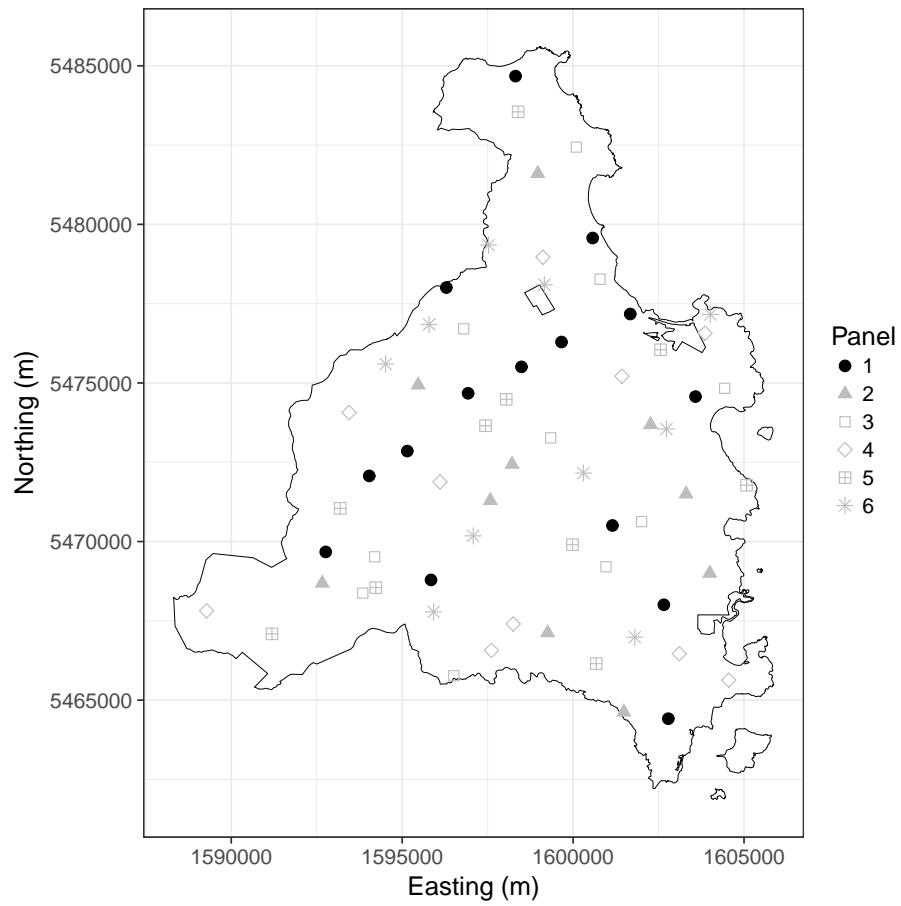


Figure 5: An example of bird monitoring in Abel Tasman National Park New Zealand. Panel 1 is measured annually while the other panels are on a 5-year rotation described as  $[1 - 0, (1 - 4)^5]$ . The first year, panels 1 and 2 would be sampled. This design gives excellent spatial coverage over the park each year ( $n = 25$ ) and over a 5-year period ( $n = 65$ ).