

¹ Using balanced acceptance sampling as a master
² 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.

²³ **Keywords:** Master Sample, Spatial Balance, Environmental Monitoring,
²⁴ Legacy Monitoring.

²⁵

1 Introduction

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

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

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

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

⁶⁴ The sampling method chosen should be flexible enough for a variety of users
⁶⁵ and study designs to be effective for coordination. Monitoring can take place
⁶⁶ 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

¹³⁶ regional and national level in New Zealand.

¹³⁷ 2 Methods

¹³⁸ 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)

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

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

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

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

¹⁴⁸ Figure 1 shows an example of how this sequence creates spread by systematically
¹⁴⁹ 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 λ 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 α 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 100×100 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

³⁰¹ probability sampling using either BAS or GRTS to augment legacy monitoring.

³⁰² **3 Application: New Zealand terrestrial monitoring**

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

³¹⁵ Ecosystems across the PCL have been identified as high priority and are
³¹⁶ labelled Ecosystem Management Units (EMUs) in response to intermediate
³¹⁷ outcome objective (IOO) 1.1 – “A full range of New Zealand’s ecosystems is
³¹⁸ conserved to a healthy functioning state” (Department of Conservation 2013).

³¹⁹ These areas are of special interest and have a high level of investment through
³²⁰ management activity. To assess the management outcomes of IOO 1.1 and re-
³²¹ port on success or adapt management for improvement, Tier 1 monitoring must

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

324 A national sample of New Zealand using BAS can make up the master
325 sample, with the existing Tier 1 points included. For efficiency each island
326 (North Island, South Island, Stewart Island, Chatham Islands, etc.) will be
327 stratified and have their own bounding box and random seed. The seed chosen
328 for the South Island was $\mathbf{u} = (4887260, 18041662)$ with minimum bounding box
329 in NZTM

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

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

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

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

337 The NEXT Foundation currently manages biodiversity at Abel Tasman Na-
338 tional Park (ATNP), one of DOC's EMUs, in a partnership with DOC. Based
339 on their agreement, the Tomorrow Accord, the NEXT Foundation is managing

³⁴⁰ ATNP while ecological integrity is in a transitional phase. DOC will take over
³⁴¹ management activity once the park is in a maintenance phase. Monitoring needs
³⁴² to be undertaken to establish the current state of ATNP and then to determine
³⁴³ when ecological integrity has been restored. One of the indicators of ecological
³⁴⁴ integrity was focussed on bird abundance and distribution through the park.

³⁴⁵ A sample size of $n_{total} = 65$ was chosen based on a precision analysis using
³⁴⁶ simr (Green & MacLeod 2016) and historical bird count data from the Eglinton
³⁴⁷ Valley. Temporal variation was expected to be less than spatial, therefore 15
³⁴⁸ samples were selected to be measured annually, and the other 50 on a rotating
³⁴⁹ 5-year panel $[1 - 0, (1 - 4)^5]$. From the Tier 1 programme mentioned above,
³⁵⁰ there were four legacy samples in the sample frame. If DOC implemented an
³⁵¹ EMU monitoring programme that had 500 augmented sites on the South Island,
³⁵² then there would be an additional seven points that were already monitored and
³⁵³ funded by DOC using the master sample. These points are included in the ro-
³⁵⁴ tating panel on years corresponding to the years they are to be sampled. See
³⁵⁵ Figure 5 for an example of the selected points in this monitoring programme.

³⁵⁶ Abel Tasman National Park is an example of localised monitoring using the
³⁵⁷ master sample that can contribute to national estimates of bird abundance and
³⁵⁸ distribution. DOC gets better precision with the increased sampling in ATNP
³⁵⁹ and the NEXT Foundation saves resources by using DOC's national investment
³⁶⁰ in monitoring explicitly in their design.

³⁶¹ The master sample above is entirely defined by the seed **u** and the bounding
³⁶² box. Hence, there is no need for a repository to hold the coordinates. Compu-

363 tationally the master sample is easy to run on the fly. Generating 65 points for
364 Abel Tasman National Park in Figure 5 takes ≈ 0.5 seconds on a desktop com-
365 puter. See supplementary materials for R script to generate a master sample in
366 New Zealand.

367 4 Discussion

368 A master sample can be a useful tool to organise environmental monitoring
369 at different spatial scales as previously done using GRTS or RRQRR (Larsen
370 *et al.* 2008; Theobald 2016). By using BAS instead of GRTS there is better
371 spatial balance (Robertson *et al.* 2013) and no need for an oversample. It is also
372 possible to add an extra dimension to do unequal probability sampling leading
373 to an overall more flexible design. Depending on the population being sampled,
374 spatial balance may or may not lead to a more precise sample than simple
375 random sampling. However, it is likely that some spatial balance will improve
376 efficiency for most designs. Not needing to oversample to create a master sample
377 using BAS means that it will remain relevant at any scale that monitoring takes
378 place no matter how localised. If an extra dimension is needed, for instance
379 to take a proportional to surface area sample across mountainous regions with
380 steep surfaces, the master sample can be adapted to incorporate this. Another
381 benefit of BAS as a master sample is that it is computationally fast and easy
382 to program. This reduces the effort needed for storing a million or more points
383 on a file for others to use. Instead a user can run a provided R script loading

384 their region as a shape file and generate their sample quickly and locally with
385 unique IDs provided to keep track of sampling.

386 In our experience, any large scale long-term monitoring will need to incor-
387 porate already existing monitoring programmes that are proven effective. This
388 was a requirement in developing a master sample for New Zealand. We have
389 shown that there is no major issue with incorporating legacy monitoring into the
390 design but recommend that all sites are rigorously vetted to ensure no known
391 biases are included if historically the sites were judgement samples or for other
392 reasons. Using panel designs can help incorporate the already existing visitation
393 schedule of the legacy plots into an efficient monitoring design. We also recom-
394 mend against incorporating legacy plots by selecting them if the BAS sample is
395 nearby, based on some criteria.

396 The master sample helps coordinate the locations sampled for environmental
397 surveys. Every survey at the local and national level should still go through
398 rigorous design. This means defining the objectives of monitoring clearly and
399 the methods to use so that they are consistent with standard methodology as
400 required by the objective. By following the steps outlined in Reynolds *et al.*
401 (2016) and using the master sample for point generation we believe that the
402 monitoring programmes undertaken at all levels will have improved efficiency
403 and contribute to the overall knowledge of the population of interest.

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500 **6 Supporting Information**

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

503 **7 Data Availability**

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

507 **8 Author Contribution**

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

₅₁₃ **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)	262.36 (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)	272.40 (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.

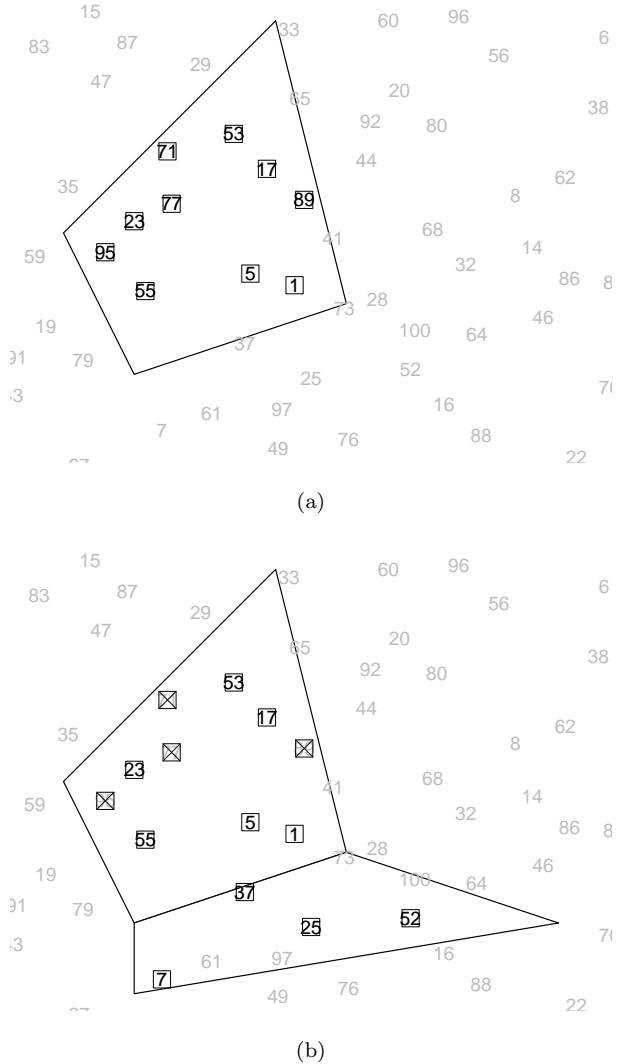


Figure 2: Example of changing boundaries using the master sample showing some of the first 100 points in $[0,1)$, the order of which is shown by the numbers. A sample of 10 is then selected in the original study (a). In (b), an area is added to the study region but resources still only allow 10 samples.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

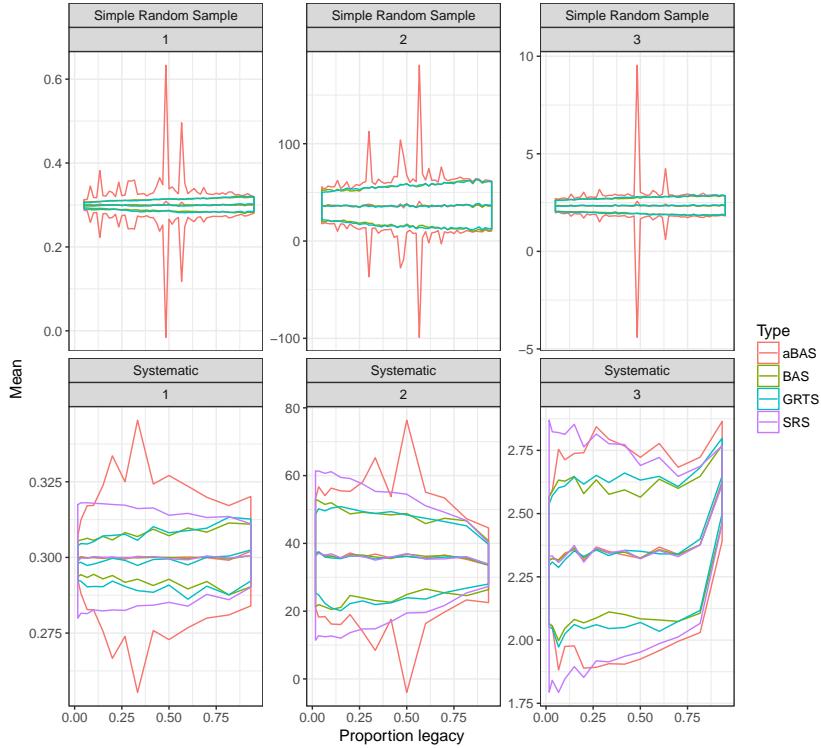
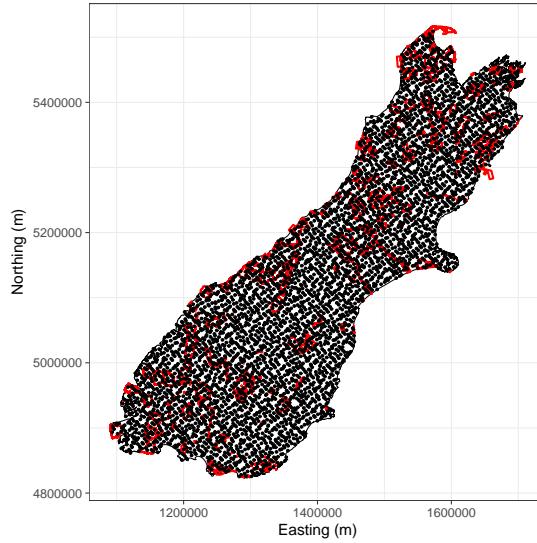
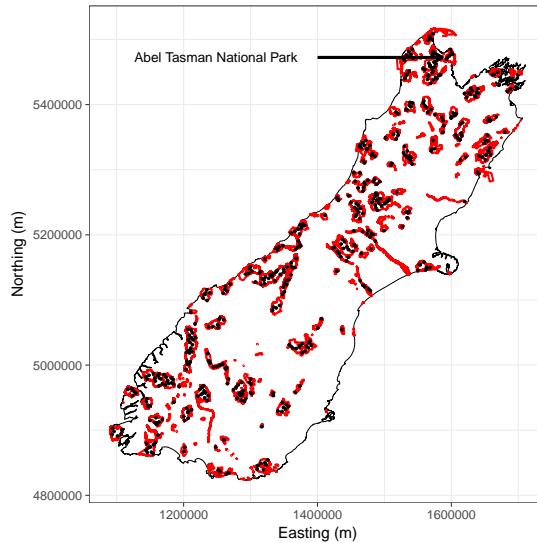


Figure 3: Results from the simulation study testing the impact of adding new samples from altered balanced acceptance sampling (aBAS), balanced acceptance sampling (BAS), generalised random tessellation stratified (GRTS), and simple random sampling (SRS) to existing legacy monitoring locations. Three 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

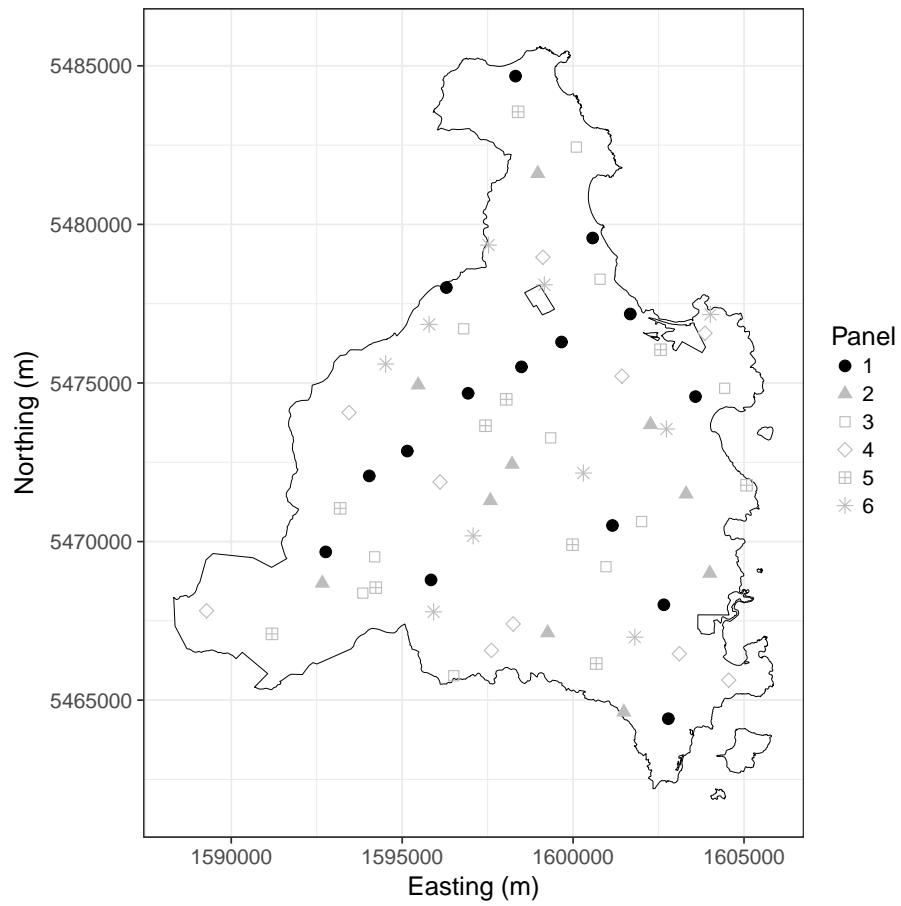


Figure 5: An example of bird monitoring in Abel Tasman National Park New Zealand. Panel 1 is measured annually while the other panels are on a 5-year rotation described as $[1 - 0, (1 - 4)^5]$. The first year, panels 1 and 2 would be sampled. This design gives excellent spatial coverage over the park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