Usefulness of an opportunistic data analysis approach to evaluate if environmental regulations aim at relevant applications

Corradini, F., González, N., Casado, F., Rojas, V., & van der Ploeg, M.

This is a "Post-Print" accepted manuscript, which has been published in "Geoderma"

This version is distributed under a non-commercial no derivatives Creative Commons

([CC-BY-NC-ND](#)) user license, which permits use, distribution, and reproduction in any medium, provided the original work is properly cited and not used for commercial purposes. Further, the restriction applies that if you remix, transform, or build upon the material, you may not distribute the modified material.

Please cite this publication as follows:

Corradini, F., González, N., Casado, F., Rojas, V., & van der Ploeg, M. (2019). Usefulness of an opportunistic data analysis approach to evaluate if environmental regulations aim at relevant applications. *Geoderma*, 351, 261-269.
<https://doi.org/10.1016/j.geoderma.2019.05.007>

1 **USEFULNESS OF AN OPPORTUNISTIC DATA ANALYSIS APPROACH TO EVALUATE IF**
2 **ENVIRONMENTAL REGULATIONS AIM AT RELEVANT APPLICATIONS**

3

4 Fabio Corradini^{1,2} • Natalia González³ • Francisco Casado² • Verónica Rojas² • Martine van der
5 Ploeg¹

6

7 ¹Soil Physics and Land Management Group, Wageningen University & Research, 6708PB
8 Wageningen, The Netherlands

9 ²Instituto de Investigaciones Agropecuarias, INIA La Platina. Casilla 439, Correo 3, Santiago, Chile

10 ³Servicio Agrícola y Ganadero, SAG Dirección Regional Metropolitana. Paseo Bulnes 140,
11 Santiago, Chile

12

13 ✉ Fabio Corradini

14 fabio.corradini@inia.cl

15 Tel: +56 2 2577 9275

16

17 **Abstract**

18 Environmental regulations aim to protect the environment from anthropogenic detrimental effects.
19 To ensure their effectivity and to avoid unexpected results and budget losses, environmental
20 regulations need careful designs grounded in observational data. Comprehensive monitoring
21 campaigns are not always achievable in developing economies, since environmental monitoring is
22 not always prioritized due to resource constraints. We propose to tackle the problem using an
23 opportunistic data analysis approach as supplementary information for environmental monitoring.
24 We applied this approach to evaluate the application of Chilean phosphorus (P) fertilization
25 subsidy. A risk assessment for P surplus was performed using three datasets: (1) secondary data
26 acquired from thousands of unclassified laboratory records from the private sector ($n = 7,957$); (2)
27 a dataset of soil available P from a budget-restricted monitoring campaign, and; (3) a conjoint
28 dataset that comprises 1 and 2. Results indicate that while laboratory records represented the
29 general characteristics of the study area, field monitoring data evidenced a surplus of soil P. Using
30 the laboratory records to enrich the data acquired by field monitoring modified the reality reflected
31 by the monitoring data alone. The use of the conjoint dataset leads to the conclusion that soils in
32 the study area had enough available P for optimum production, and that farmers were already
33 using external sources of P fertilizers within the current market structure. Our study constitutes an
34 example of the use of private data to contribute to public soil monitoring programs and
35 environmental regulation designs. The case study serves as a successful example of opportunistic
36 data usage in environmental monitoring, as a low-cost alternative to complement field
37 observations.

38

39 **Keywords**

40 Opportunistic data • Soil monitoring • Phosphorus surplus • Chilean soils • Environmental
41 regulation

42

43 **1 Introduction**

44 Environmental regulation is important as it protects the environment from the detrimental effects of
45 human activities, aiming at population safety (Sullivan et al., 2018). As part of the task of
46 environmental regulation, subsidies in agriculture target social protection from deprivation and
47 scarcity, environmental sustainability, and improved productivity (Tirivayi et al., 2016). In
48 developing economies public expenditures mostly focus on the productive sector, where a larger
49 fraction of the total budget is used in agriculture (Yu et al., 2015). Social protection and agriculture
50 become interrelated processes, demanding limited resources that are not always available
51 (Fiszbein et al., 2014; Lowder et al., 2017).

52 Agricultural subsidies are often oriented toward conservation practices to avoid environmental
53 detriments. While ecosystem protection and restoration has been embraced by the international
54 community through the United Nations Sustainable Development Goals, farmers could be reluctant
55 to use environmental-favourable land managements (Floress et al., 2018). This has caused the
56 implementation of top-down policies where farmers adopt new practices when direct rewards, such
57 as subsidies, are in sight (Tarfasa et al., 2018). As in this way subsidies can become the goal of
58 the practice, the end result is usually undermined, with studies showing farmers doing the bare
59 minimum to get the subsidies going (Auerswald et al., 2018). Therefore, agricultural subsidies need
60 careful designs and evaluations to avoid unexpected results and budget losses (Mason et al.,
61 2013; Nyssen et al., 2017).

62 Nutrient depletion constitutes a symptom of land degradation, therefore subsidies for fertilizer
63 acquisition could be intended as compatible with conservation practices (Koppmair et al., 2017).

64 Fertilizers subsidies are relevant in developing economies where a negative feedback describes
65 the relation between low soil fertility and poverty (Barrett and Bevis, 2015). Although it is an
66 attractive measure for policy makers in growing economies, giving subsidies for fertilizer
67 applications has detractors reporting numerous cases of failure (Holden and Lunduka, 2014;
68 Mason and Jayne, 2013; Nyssen et al., 2017). When applied within a frame of additional
69 interventions that increase soil fertility, subsidizing fertilizers applications presents a tempting
70 solution for limited public budget since two problems, poverty and land degradation, are tackled at
71 the same time (Ricker-Gilbert and Jayne, 2017).

72 Designing relevant fertilizer subsidy programs should consider the current status of soil fertility.
73 While poor soil fertility may lead to poverty, fertilization excess poses a threat to environmental
74 health (Dupas et al., 2015; Fischer et al., 2017; Watson et al., 2007). Monitoring the status of soil
75 fertility could be covered by extensive monitoring programs, but these demand resources that are
76 often not foreseen in research budgets. Yet, data availability can be broadened if alternative data
77 sources are used in an opportunistic data analysis approach. The opportunistic approach refers to
78 the use of any data that have been collected without standardized protocols (opportunistic data),
79 having incomplete observations or absent accompanying data, but which may, nonetheless,
80 constitute a research prospect (Silvertown, 2009). Although the lack of metadata usually makes
81 opportunistic data unreliable, when these alternative data sources are coupled with data gathered
82 under proper scientific aims, the opportunistic data approach reduce research costs, and can
83 improve monitoring results (Giraud et al., 2016).

84 Although the use of an opportunistic data approach is increasing in ecology and environmental
85 monitoring (Abbott et al., 2018; Lots et al., 2017), it has not been used for evaluating the relevance
86 of environmental regulations. Therefore, we investigated if an opportunistic data approach can be
87 used to assess the relevance of environmental regulations, using opportunistic data as low-cost
88 ancillary information in factual monitoring campaigns. To test the idea a Chilean case study is
89 provided. Chile presents an agricultural subsidy regulation completely oriented to soil conservation
90 practices (Ministerio de Agricultura, 2010), including subsidies to fertilization practices, with the
91 scope of promoting integral management plans that prevent soil erosion. The aim of this paper is to
92 test if an opportunistic data approach is useful to evaluate the application relevance of a
93 phosphorus (P) fertilization subsidy from the Chilean government. We will do so using three
94 datasets with different structural characteristics to determine the soil P status. The first dataset
95 comprises the records for soil available P of a regional soil laboratory, standing as opportunistic
96 data as it does not include accompanying information. The second dataset includes soil P data
97 from a time-restricted monitoring campaign (factual monitoring data), and the third conjoins both.
98 Each data set will be used in a risk assessment to evaluate the probability of P deficit/surplus,
99 assessing by this means the relevance of the subsidy application.

101 **2 Material and methods**

102 2.1 Study area

103 The study took place in the Chilean Metropolitana Region, an area of 15,400 km² located in the
104 north of the Chilean Central Valley. As this region is located between the Andean and the Coastal
105 mountain ranges only 2,770 km², less than 20%, of the surface corresponds to agricultural fields.
106 The study area included arable soils and forage prairies of moderate slopes where commercial
107 agriculture is performed, comprising a total area of 2,273 km² (Fig. 1 Interactive map). Natural
108 grazing prairies and marginal soils (<75 cm depth, stoniness > 30%, and slope > 5%) were
109 excluded.
110 The climate according to Köppen-Geiger climate classification is warm temperate with warm
111 summers and low precipitation (Csb) (Kottek et al., 2006). There is, however, a transition to an arid
112 climate (BSk) towards the North of the valley. Mean annual precipitation is about 300 mm, and the
113 average annual temperature is 15 °C, with 23 °C maxima and 10 °C minima (Dirección
114 Meteorológica de Chile, 2010-2016). The climate dictates that the soils within the study area
115 present a xeric moisture regime and a thermic temperature regime (CIREN, 1996). There are five
116 soil orders within the study area, from which Mollisol predominates encompassing 70% of the total
117 area. Other soil orders are Alfisols (11%), Inceptisols (13%), Entisols (2%), and Vertisols (4%). Soil
118 suborders, great groups, and subgroups are indicated in the Interactive Map (Fig. 1) and the area
119 of each is shown in the supplementary material (S1).

120

121 2.2 Environmental regulation: the P subsidy

122 The Chilean soil restoration program was originated when the country joined the MERCOSUR in
123 the 90s. At that time, there was pressure from the productive sector to include measures that
124 targeted both production and restoration. It was expected that the elimination of customs duties
125 and tariff restrictions on the circulation of goods would affect local production. Therefore, while the
126 main aim of the program was to protect soil from degradation, policymakers had to include
127 subsidies to protect and support national agricultural activities (Caro et al., 2006). The duality of the
128 program aim stands out in the official definition of degraded soil: 'Soils that due to lack of
129 phosphorus, excess acidity, levels of erosion, deterioration of vegetation cover or to other physical,

130 chemical or structural limitations for their occupation, cannot be used efficiently in a sustainable
131 way in agricultural production' (Ministerio de Agricultura, 1999).

132 Nowadays, the soil restoration program allows farmers to decide freely on the managements for
133 which they want funds for by choosing through a given list of possibilities (see the supplementary
134 material for the complete list S2). There are two elements that stand out from the list. First, the
135 application of fertilizers is included within soil restoration practices, which reflects back to the
136 double goal of the policy. Second, P applications are placed in a different cluster than the
137 application of other chemical elements (K, Ca, and S).

138 Before its implementation at national level, the program was meant for the southern part of the
139 country, where livestock activities take place on Andisols where P is easily fixed (Casanova et al.,
140 2013). The original practices were bounded to this original intention. Later, when the program was
141 extended to the whole country, it was reviewed by a joint committee. The committee included
142 representatives of the productive sector and government productive development organizations.
143 Additional practices were included, but none of the first was omitted. As a result, the P subsidy was
144 kept within the list of fundable practices. Through the program, the government subsidizes
145 phosphorus (P) applications when soil available P drops below 20 mg kg⁻¹ (based on the Olsen
146 method). This work was framed within the aim of the government to avoid a P deficit scenario, thus
147 the 20 mg P-Olsen kg⁻¹ were used as a threshold in a risk assessment approach.

148

149 2.3 Opportunistic dataset

150 Through their Soil and Plant Nutrition Laboratory located in the La Platina Regional Research
151 Centre, the Agricultural Research Institute (INIA) provides analytical services to both farmers and
152 researchers/scientists from the Chilean Central Valley. Rarely, clients corresponds to small
153 farmers, being the service required mostly by big producers (>20 ha), governmental institutions,
154 and researchers. The customer profile implies that generally the location of the sites where the
155 samples are taken is not reported. Clients usually present only a commercial address in the capital
156 for sending the results when ready. Small producers send samples for analysis only when they are
157 motivated by operators of governmental agricultural extension programs, who act as mediators
158 darkening once again the provenience of soil samples. In this way, farmers that do not present

adequate soil management practices -among who the government should promote practices to avoid environmental detriments- are possibly underrepresented.

Analytical reports from 2005 to 2015 were coerced into a single dataset (INIA dataset). The database built constitutes opportunistic data as the records that it contains were not collected aiming at monitoring soil nutrient status at any particular scale. The INIA dataset holds observations of soil chemical properties from samples that were taken in unknown locations of the country Central Valley without standardized protocols or sampling designs, and that may or may not have being part of research. Therefore, the dataset is characterized by a complete lack of accompanying geographical data, including for each entry only a vague temporal reference of when (year) the soil analysis were performed (not when the samples were collected).

169

2.4 Soil monitoring dataset

2.4.1 Data collection

Sampling points were distributed within the study area using a conditioned Latin hypercube sampling (cLHS) algorithm, which proposes to stratify sampling according to exhaustive ancillary data (Minasny and McBratney, 2006). The algorithm provides a full coverage of the range of each variable, assuring representativeness of the underlying information. To this purpose, the R package '*clhs*' (conditional Latin hypercube sampling) was used (Roudier, 2017; Roudier et al., 2012). The accompanying data used to condition the sampling locations were elevation (The National Aeronautics and Space Administration and Ministry of Economy Trade and Industry, 2011), land use (CONAF and CIREN, 2013), and soil orders and aptitude for agricultural use provided by Chilean soil survey maps (CIREN, 1996). The aptitude for agricultural use is a local index given in Chilean soil survey maps to identify the overall capability of a given soil series for crop production. They aggregate the information of soil depth, slope, drainage, texture, and abundance of rock fragments (as texture modifiers), and are described by CIREN (1996). A total of 484 sampling locations were distributed along the study area. The distribution of the sampling locations by soil order, suborder, great group, and subgroup is shown in the supplementary material (S1).

187 Samples were collected between the third week of November and the last of December 2016. The
188 time of the year corresponds with the growing season, thus fertilization and irrigation programs are
189 in operation. The sample locations determined by cLHS algorithm were checked and modified as
190 needed at the time of sampling. Sampling under unrepresentative conditions (points near field
191 borders, drains, livestock shelters, etc.) was avoided, modifying pre-locations accordingly. Every
192 sampling point was georeferenced. Each sample was composed of three subsamples taken 5 m
193 apart from its sampling point, at the vertices of an equilateral triangle, being the georeferenced
194 location the barycentre. Similar sampling procedures are reported by Kelepertzis (2014).
195 Subsamples were taken with a shovel from the topsoil (0 to 20 cm depth) and homogenized in
196 plastic pails. Composite samples of 1 kg were extracted from the pails, stored in plastic bags, and
197 transported to the Soil and Plant Nutrition Laboratory at INIA, for further analysis.

198

199 *2.4.2 Soil samples analysis*

200 Soil samples were dried in a forced air oven at 40 ± 5 °C until they reached a constant weight
201 (model 1390FX, Sheldon Manufacturing). Dried samples were sieved at 2 mm and stored in plastic
202 flasks. Every sample was analysed for available P and P buffer capacity.

203 Soils in this section of Chilean Central valley are neutral to alkaline and might present CaCO_3
204 (Casanova et al., 2013; CIREN, 1996), thus soil testing for available P was determined (mg kg^{-1})
205 using the Olsen method (P-Olsen) (Olsen et al., 1954) as described by Sadzawka et al. (2006).
206 Chilean standard laboratory procedures propose a chemical analysis to quantify P fixation, known
207 as soil P buffer capacity (P-Buffer). The method consists of incubating soil at 60 °C for 24 hours
208 with and without addition of P (200 mg kg^{-1}) to then quantify available P by the Olsen extraction.
209 The difference in available P between the sample treatments (with and without P addition) are then
210 used to estimate soil P fixation. Results are reported as the amount of P (kg) needed to increase
211 one unit of P-Olsen (mg kg^{-1}) in one hectare of soil, considering a sampling depth of 20 cm
212 (Sadzawka et al. 2006). To our knowledge the method has had only a regional use, and is
213 nowadays used in Chile to make fertilizer dose recommendations to farmers.

214

215 *2.4.3 Quality control*

216 Soil samples from Wageningen Evaluating programs for Analytical Laboratories (WEPAL) were
217 used as reference material to check P-Olsen determination accuracy. WEPAL provide soil samples
218 which chemical composition has been retrieved from analytical results provided by several
219 laboratories around the world. Every laboratory uses similar determination procedures, sample
220 preparation, and technical equipment. As a criteria, results from reference samples were within one
221 standard deviation of the reported WEPAL value. Furthermore, 20% of samples were analysed in
222 duplicate seeking less than 10% variation, according to the inherent repeatability of the method
223 reported by Sadzawka et al. (2006).

224 All reagents used were analytical grade and were obtained from Merck KGaA. The sulphuric acid
225 used in the preparation of the molybdenum blue solution was ultrapure quality. The calibration
226 standards of P were prepared by appropriately diluting stock solutions of 1000 mg L⁻¹. The
227 activated charcoal used during the filtration process was treated to get a blank absorbance less
228 than 0.015 units. All solutions were prepared with ultrapure water from a nanopure system
229 (Barnstead E-Pure D4642, Thermo Fisher). All glassware and polyethylene bottles were cleaned
230 by soaking in a 10% (v/v) HNO₃ solution followed by three rinses with deionized water.

231

232 2.5 Statistical analysis

233 2.5.1 *Opportunistic dataset*

234 The INIA dataset did not contain P-Buffer records, thus only P-Olsen was analysed. Descriptive
235 statistics for the data entries of P-Olsen within INIA dataset were generated (mean, median,
236 variance, and quantiles). Data were log-transformed and its normality tested by Shapiro-Wilk
237 normality test. As log-transformed data showed a good approximation to a normal distribution, a
238 normal distribution was parametrized by bootstrapping the mean and standard deviation from INIA
239 dataset entries. One thousand sub-samples of 100 data entries were generated to estimate each
240 statistical parameter. Descriptive statistics were calculated for the mean (μ) and the precision ($\tau =$
241 $1/\sigma^2$). Shapiro-Wilk test was used to test the normality of the simulated μ values, while a gamma
242 distribution was fitted by maximum likelihood estimation (MLE) to τ . The probability for a random
243 observation to be above the 20 mg P-Olsen kg⁻¹ was assessed by a Monte Carlo approach,

244 sampling random values of μ and τ from their probability functions. The Monte Carlo simulation
245 was used to generate 1000 possible scenarios that were summarized using descriptive statistics.

246

247 *2.5.2 Soil monitoring dataset*

248 Soil field data were analysed according to frequentist procedures. Descriptive statistics for P-Olsen
249 concentrations were calculated. Concentrations were log-transformed, and the normality of the
250 data tested by Shapiro-Wilk. As P-Olsen concentrations were log-normally distributed, their mean
251 and standard deviation calculated as part of the descriptive statistics were used to estimate the
252 probability of a random sample to surpass the 20 mg P-Olsen kg⁻¹ threshold.

253 P-Buffer did not show a known pattern, therefore, an empirical cumulative distribution function
254 (ECDF) of its expected values was calculated. An empirical cumulative distribution function ranks
255 the empirical observations assigning a cumulative probability to each observation equal to the
256 fraction of observations till its ranked position. The median, mean and quantiles were calculated for
257 P-Buffer to characterize its statistical dispersion.

258 As available P and P saturation are known to be related (Allen and Mallarino, 2006; Fischer et al.,
259 2017), the correlation between P-Olsen and P-Buffer was tested using the Pearson correlation
260 coefficient (r).

261 To evaluate the influence of different soil conditions over P-Olsen concentration north-south and
262 east-west spatial transects were plotted to address its spatial distribution. In this evaluation, land
263 use was used as a factor, and block means were added every 3 km.

264

265 *2.5.3 Conjoint dataset*

266 Bayesian statistics take into account prior knowledge or beliefs about a phenomenon to update
267 that knowledge using new data (a posterior knowledge, simply called posterior). We used this
268 approach to integrate the opportunistic data with the field data. To this goal, the INIA dataset was
269 used to define a prior belief of soil P status within the study area, to then update the belief using
270 the soil monitoring dataset as new information. We will refer to this procedure from now on as an
271 opportunistic data analysis approach since the data from the factual monitoring campaign is

272 analysed under the light of the opportunistic dataset. As mention in section 2.6.1 the approach was
 273 used only for P-Olsen, since there were no entries for P-Buffer in the INIA dataset to define a prior.
 274 To obtain the posterior distribution, a likelihood function that relates the prior parameters to the
 275 studied phenomenon has to be established before calculations. The posterior distribution is then
 276 the product of the prior distribution and the likelihood function. In this study, the likelihood function
 277 and its parameters were defined analysing the entries from the INIA database. As pointed in
 278 section 2.6.1, in central Chile soil (log-transformed) P-Olsen is normally distributed. Therefore, the
 279 conditional distribution of the field data (y), given the mean (μ) and precision (τ) parameters, is $p(y |$
 280 $\mu, \tau) = N(\mu, 1/\tau)$. Estimating the parameters of a normal distribution using Bayesian inference and
 281 conjugated priors is a common approach (see Gelman et al. (2013) for a complete explanation).
 282 Here, the use of a conjugate prior presents the advantage that the posterior distribution (i.e. the
 283 parametrised normal distribution) has a known form (the same as the prior), making the parameter
 284 estimation a deterministic process.
 285 As the mean (μ) and precision (τ) of the proposed normal distribution are unknown, the
 286 corresponding conjugated prior is the Normal-Gamma distribution that has the form $p(\mu, \tau | \mu_0, k_0,$
 287 $\alpha_0, \beta_0) = N(\mu | \mu_0, (k_0 \tau)^{-1})Ga(\tau | \alpha_0, \beta_0)$. In this prior distribution, the mean (μ) and precision (τ)
 288 parameters of the normally distributed observations are drawn respectively from a normal
 289 distribution with mean μ_0 and variance $(k_0 \tau)^{-1}$, and from a gamma distribution with shape α_0 and rate
 290 β_0 which defines τ . The k_0 parameter is the equivalent sample size of the prior distribution (i.e.
 291 $var(\mu | \tau) = 1/(k_0 \tau)$), and represents the prior belief about μ .
 292 With both prior distribution and likelihood defined, random samples from the posterior distribution
 293 were drawn using the field data. By this means, different scenarios of soil P status were generated
 294 for the study area (random values of μ and τ) to compute the probability of having concentrations
 295 greater than 20 mg kg⁻¹. The scenarios drawn were summarized by descriptive statistics (median,
 296 mean, and quantiles).
 297 To check whether soil orders have differences in P-Olsen, the monitoring dataset was split in two,
 298 having Mollisols and other soil orders as the two levels. Sampling from the data subsets, two new
 299 posteriors were defined using the same prior distribution and likelihood function defined previously
 300 with the opportunistic dataset. Differences between the posteriors were evaluated by 1,000 random

301 throws as $T = p(\mu_{\text{mollisols}} > \mu_{\text{other orders}})$, were an average T value approximating 0.5 mean low
302 differences between factors, and $\mu_{\text{mollisols}}$ and $\mu_{\text{other orders}}$ stand for the posterior mean of the different
303 soil orders. As the data were unbalanced, the subset of Mollisols ($n = 306$) was resampled to
304 match the quantity of observations of the other soil orders ($n = 178$). The process of resampling
305 and testing the means was repeated 1,000 times. The results of the 1,000 replications of the
306 $p(\mu_{\text{mollisols}} > \mu_{\text{other orders}})$ test was summarized using descriptive statistics.

307

308 *2.5.4 Statistical software*

309 Statistical analysis were performed in the R environment (R Core Team, 2017). The packages
310 'raster' (Hijmans, 2017) and 'rgdal' (Bivand et al., 2017) were used in combination with QGIS
311 2.18.2 (QGIS Development Team, 2017) to manipulate spatial data. The package 'MASS'
312 (Venables and Ripley, 2002) was used to perform MLE estimations when needed.

313

314 **3 Results**

315 **3.1 Opportunistic data**

316 The INIA dataset had 7,957 entries for P-Olsen, and zero for P-Buffer. Although data of P-Olsen
317 concentrations present a slight right skewness when centred, scaled and log-transformed, a log-
318 normal distribution explains with sufficiency the expected values for P-Olsen. Figure 2 presents the
319 histogram for P-Olsen values within INIA database, and the density of a normal distribution.

320 Consequently, P-Olsen concentrations were log-transformed ($\ln$) in further calculations.

321 Normal distributions are characterised by two parameters, the mean (μ) and the precision (τ), that
322 can be drawn by bootstrapping from the INIA database observations. The bootstrapped values are
323 used to define each parameter (μ and τ) expected distribution. Table 1 presents descriptive
324 statistics for the bootstrapped μ and τ and Fig. 3 shows their histograms and theoretical distribution
325 densities. The mean concentration was normally distributed (Shapiro-Wilk p-value = 0.517) as $p(\mu |$
326 $\mu_m, \sigma_m^2) = N(\mu_m = 3.09, \sigma_m^2 = 0.015)$, where μ stands for a random observation of the sample mean
327 given μ_m and σ_m^2 as mean and variance parameters of a normal distribution (N). Similarly, the
328 precision τ ($1/\sigma^2$) for P-Olsen concentration followed the gamma distribution as $p(\tau | \alpha, \beta) = \text{Ga}(\alpha =$
329 $29, \beta = 46)$, where τ stands for a random observation of a sample precision given α and β as shape

330 and rate parameters of the gamma distribution (Ga). Having the probability distributions defined for
331 both μ and τ , the probability of surpassing the P-Olsen concentration threshold of 20 mg kg⁻¹
332 ($\ln(20) = 2.99$) was 53%.

333

334 3.2 Soil monitoring

335 Similarly, the measurements of P-Olsen concentration for the field data can be represented by a
336 log-normal distribution (Fig. 2). The observed mean and precision were higher than that showed by
337 the INIA dataset, indicating that P-Olsen concentrations are expected to be higher without
338 presenting a large variation (Table 1). Moreover, the probability of surpassing the P-Olsen
339 threshold of 20 mg kg⁻¹ was higher than that of the opportunistic data, rising up to nearly 80% of
340 chances (17% increase).

341 The observed mean for P-Buffer was 6.6 kg P ha⁻¹, with a standard deviation of 6.7 kg P ha⁻¹. The
342 distribution of observations did not approached a normal distribution, even when the data were log-
343 transformed. The gamma distribution also failed to represent the field observations. Therefore, a
344 better characterization of the observed values is given by measures of statistical dispersion
345 different than μ and τ . The field data presented a median of 5.4 kg P ha⁻¹, an interquartile range of
346 1.9 kg P ha⁻¹, and a 95% CI that ranged between 2.5 and 19.5 kg P ha⁻¹ (Table 1). The ECDF
347 function was estimated to calculate expected probabilities for a given P-Buffer value (Fig. 4). There
348 was not a significant correlation between P-Olsen concentrations and P-Buffer ($r = 0.23$).

349 Regarding the spatial distribution of the studied variables, both P-Olsen and P-Buffer did not
350 presented a clear spatial pattern. Figure 5 present the distribution of P-Olsen concentration within
351 the studied area including general east/south transects. Observations were commonly above the
352 20 mg kg⁻¹ threshold and presented a slight increase towards the south.

353

354 3.3 Opportunistic data analysis approach: Expected P-Olsen

355 The $p(\text{P-Olsen} > 20 \text{ mg kg}^{-1}) = 0.53$ that the INIA dataset presents is no more than a guess of $p(\text{P-}$
356 $\text{Olsen} > 20)$ for the Chilean Central Valley. The sampling campaign was focused within the study
357 area, and corresponds to 484 sampling points, which suggest that $p(\text{P-Olsen} > 20 \text{ mg kg}^{-1}) = 0.79$.
358 As it could be argued that it is a small dataset, we explore an alternative (opportunistic approach)

359 to conjoin the two. The conjunction procedure take the general guess for the whole Central Valley
 360 and focus it within the study area. Which is where the subsidy is meant to be applied.
 361 The values of the prior parameters (μ_0 , α_0 , and β_0) were calculated using the INIA database,
 362 resulting $\mu_0 = 3.09$, $\alpha_0 = 29$, and $\beta_0 = 46$ (see section 3.1). The k_0 parameter was estimated using
 363 the relation $k_0 = (\sigma^2\tau)^{-1} = 105$, where $\sigma^2 = \sigma_m^2 = 0.015$, and $\tau = 0.63$, which is the expected mean for
 364 the prior gamma distribution defined for the precision of P-Olsen concentrations (in a gamma
 365 distribution $E[x] = \alpha/\beta$, which in this case is $29/46 = 0.63$).

366 As mentioned, when using a conjugate prior distribution the derived posterior distribution takes the
 367 same form, which corresponds to the Normal-Gamma distribution $p(\mu, \tau | y) = N(\mu | \mu_n, (k_n \tau)^{-1})Ga(\tau$
 368 $| \alpha_n, \beta_n)$. Here the mean (μ) and precision (τ) parameters of the normally distributed observations
 369 given the field data (y), are drawn respectively from a normal distribution with mean μ_n and
 370 variance $(k_n \tau)^{-1}$, and form a gamma distribution with shape α_n and rate β_n . Using the prior
 371 parameters from the INIA database and the field data, the posterior distribution parameters μ_n , k_n ,
 372 α_n , and β_n , can be calculated as

$$373 \mu_n = (k_0\mu_0 + n\bar{x})/(k_0 + n)$$

$$374 k_n = k_0 + n$$

$$375 \alpha_n = \alpha_0 + n/2$$

$$376 \beta_n = \beta_0 + \frac{1}{2} \sum_{i=1}^n (x_i - \bar{x})^2 + \frac{k_0 n (\bar{x} - \mu_0)^2}{2(k_0 + n)}$$

377 Where n is the data size, and $\bar{x}$ and x_i the average and i observation of the field data, respectively.
 378 By this, the obtained posterior distribution parameters were $\mu_n = 3.61$, $k_n = 589$, $\alpha_n = 271$, $\beta_n = 260$.
 379 As the estimated parameters μ and τ are drawn from a probability distribution (Normal-Gamma),
 380 they have a range of probable values. Table 1 presents the mean, median and quantiles for μ and
 381 τ . Sampling from the posterior distribution random values for μ and τ , an average cumulative
 382 distribution function (CDF) with a 95% confidence interval was estimated for P-Olsen expected
 383 concentration within the study area (Fig. 6). The average probability of having a random soil
 384 sample presenting a P-Olsen concentration above 20 mg kg^{-1} was 0.73 (CI = $0.70 - 0.76$)
 385 according to the estimated CDF.

386 There were no differences of P-Olsen between Mollisols and other soil orders. The $p(\mu_{\text{mollisols}} >$
387 $\mu_{\text{other orders}})$ was equal to 0.56 ± 0.12 , with a 95% interval of $0.31 - 0.77$.

388

389 **4 Discussion**

390 4.1 Using an opportunistic data analysis approach in environmental monitoring

391 The use of opportunistic data to enrich field monitoring modifies the reality reflected by field data
392 alone. This is expected in Bayesian inference when informative priors are used (Cowles, 2013). To
393 begin with, changes in the results comprised an increase of the uncertainty in the estimations,
394 including it in the output and therefore aggregating new possible interpretations to data (Krueger,
395 2017). This extra noise is expected since opportunistic data have limited explanatory variables.
396 Secondly, it is important to stress that changes in results are not due to the different statistical
397 approaches followed. Bayesian and frequentists data analysis approaches are both expected to
398 converge when uninformative priors are used –as if in the study case opportunistic data would not
399 have been included (Cowles, 2013). Therefore the changes are an exclusive product of the
400 coupling of soil monitoring data with opportunistic data.

401 Differences between reliable and opportunistic data have been interpreted before in scientific
402 literature as a positive result (Giraud et al., 2016). In fact, the differences validates the use of
403 opportunistic data as supplementary information (Lima et al., 2017). The enhancement in the
404 output interpretations can be unveiled when the spatio-temporal characteristics of the datasets
405 comprised in the case study are analysed. The INIA dataset has no explanatory variables, which is
406 known to complicate the drawing of probable causes in observational studies (e.g. Lots et al.,
407 2017). In this way, the INIA database only gathers general information through time within the
408 study area. Information that might or might not comprise all soil types, land uses, and land
409 managements within the basin. While for the study case soil samples present a known location in
410 space, they were collected at one given moment in time and under limited land use scenarios. The
411 soil monitoring data neglect, therefore, the general soil P status of the basin and the changes that it
412 can present through time. To summarize, the INIA dataset expanded the possibilities of the field
413 dataset, including background information of soil types and land uses that would otherwise be

absent. Conversely, using only the INIA dataset for statistical inference would overlooked the main recipients of the intended subsidy (farmers).

While the use of opportunistic data analysis within the context of environmental monitoring is not new, this is a new insight for soil monitoring. During the last years, with the increase of communication technologies and internet access researches have shown a renewed interest for opportunistic data (Silvertown, 2009). This information source have been mostly used in ecological sciences, where citizen science programs are the most recognizable face (Giraud et al., 2016; Tulloch et al., 2013). Although volunteers base science have also shown good results in environmental monitoring programs (Abbott et al., 2018; Lots et al., 2017), unsteady contribution can jeopardize the results especially when monitoring is only sustained by opportunistic data (Diner et al., 2018). Using information from public and private institutions that gather it from services provision, could be a steady alternative.

The use of Bayesian inference in environmental monitoring where data availability is restricted or has low-resolution has been useful in hydrological studies (Krueger, 2017). When information gathering is a limitation for hydrological monitoring purposes, assessing the uncertainty in estimating environmental variables is a desirable output (Lima et al., 2017). Whereas some studies restrict the data inputs only to trustworthy sources, others enrich the analysis with second data sources or opportunistic data (Abbott et al., 2018). Is the conjunction of opportunistic data and data with knowing sampling efforts (or locations in this case) which confer strength to the monitoring outputs (Giraud et al., 2016). Our study exemplifies this strengthening.

The soil monitoring dataset stands for a particular sampling time during the growing season, when fertilizers are being actively applied. However, within the study area there are several different agricultural schemes such as winter crops, cover crops, fallow systems, trees (deciduous and perennial), and so forth. As a growing season is a mere concept at a regional scale, a sampling designed to include all management scenarios will be forced to address a time component, which means a permanent monitoring effort. As extensive monitoring programs demands resources that are often not foreseen in the governmental research budgets of developing economies, there is a limitation for this methodology. The opportunistic data analysis approach allows interpreting the soil monitoring dataset, as it encompasses a time component (i.e. the laboratory records).

443 Correspondingly, the approach allows to evaluate the steady condition reported by the INIA
444 dataset when the agricultural practices are performed by the intended recipients of the subsidy.

445

446 4.2 Effectivity of a P fertilization subsidy: the case study

447 The opportunistic data analysis approach suggest that within the study area there is enough soil
448 available phosphorus, therefore the subsidy seems unnecessary for nearly three quarters of the
449 soils. This implies that resources could be spent in other, more critical, necessities. As the subsidy
450 threshold of 20 mg kg⁻¹ was set by a technical committee according to plant responses to P
451 applications in the Chilean Central Valley (Ministerio de Agricultura, 2015), not only the subsidy is
452 unnecessary but any additional soil P applications.

453 Phosphorus surplus is also supported by the spatial distribution of P-Olsen of soil monitoring data
454 and by the lack of differences between soil orders. Along the study area different parent materials,
455 climatic conditions, and soil orders are present (Casanova et al., 2013), which were not
456 conditioning the observations. As soil orders should condition P availability (Daly et al., 2015), the
457 P fertilizer surplus hypothesis seems plausible.

458 The implication of the findings are double. On one hand, the subsidy is not needed because of the
459 P surplus that affects the study area. On the other, results suggests that farmers apply P fertilizers
460 as part of their agricultural management practices, being they behave independent of the subsidy
461 application. Therefore, the subsidy is doubly unnecessary, since there is no management practice
462 that needs stimulation nor productivity gain. On the contrary, high levels of soil P represent an
463 environmental threat (Roberts et al., 2017; Torrent et al., 2007), compromising the true goal of
464 Chilean agricultural subsidy policy.

465 Tangentially the case study is an example of how environmental regulations can sabotage
466 themselves by not including proper monitoring variables. Although the methodology to quantify P-
467 Buffer correspond to a local standard analysis (Sadzawka et al., 2006), there were zero entries for
468 this variable in the INIA dataset. The P-Buffer analysis had, therefore, little impact in the risk
469 assessment, because there were no references available to interpret the data. The direct
470 implication is that soil P saturation was not evaluated, which is an important factor to consider
471 when evaluating the impact of the subsidy. While monitoring soil P saturation is relevant for

472 environmental safety (Ketterings and Czymmek, 2012; Ribey and O'Halloran, 2016; Williams et al.,
473 2015), continuous monitoring campaigns for this variable in Chile are absent.

474 The Chilean regulation proposes to evaluate soil P-Olsen as an assessing tool for go/no-go
475 subsidy decisions. However, P-Olsen is not a measure of P saturation, and its transformation to a
476 P saturation measure through pedotransfer functions cannot be trusted (Fischer et al., 2017). By
477 this means, only a productive variable has been incorporated to the current regulation, neglecting
478 its environmental inspiration.

479 The dissonance observed between regulations and requested services of P-Buffer reveals a
480 tangential benefit of joining field and opportunistic data. While regulations expect that land
481 managers and owners care for the environmental status of their land establishing a formal method
482 to address that status (P-Buffer analysis), actual laboratory requests showed an overwhelming
483 indifference towards the proposed method. Soil monitoring *per se* would not point out the situation,
484 as it will recognise P saturation while neglecting the attitude of land managers.

485

486 4.3 Usefulness of the opportunistic data analysis approach

487 Reliable data are a must in science and environmental monitoring. Tidy and well-designed
488 databases are fundamental to trustworthy results. Therefore, environmental monitoring should
489 focus in the acquisition of high quality data. In our study, we used the conditioned Latin Hypercube
490 Algorithm to define a sample campaign that leaved no areas unrepresented. But however solid a
491 one-time monitoring campaign can be, it only yields a fixed value based in frequency. Therefore,
492 prior knowledge of the area could be used to enhance the result (Bayesian interpretation of
493 probability). Ideally, the prior knowledge should be another reliable dataset, which holds the results
494 of previous scientific observations.

495 However, access to tidy and highly reliable data is not always possible. In that case, the use of
496 third party data could be helpful to define the prior expectations for an area. In this regard, our data
497 supported that the approach used was useful at evaluating the environmental regulation with
498 current data availability. Nevertheless, it is evident that the need for the opportunistic approach
499 exposes structural problems in data collection and organization, and soil testing. The INIA dataset
500 shows how soil testing can be jeopardized when the focus is placed on the tests itself, ignoring

501 locations, time and manner of sampling. The current procedure yields data that are only used for a
502 certain client not allowing extrapolations or monitoring. If the laboratory had recorded explanatory
503 data, the entire approach would not have been necessary. Soil samples would only have to be
504 taken at underrepresented areas.

505 In this regard, the case study is an example of the problems to be faced when reliable data
506 sources are lacking. INIA laboratory reports were not intended for data aggregation thus time and
507 resources were designated to build the dataset. To avoid time consuming data gathering
508 processes and to allow dynamic assessments should be the focus of data collaboration networks.
509 In our work only one of the operating soil laboratories of Chilean central valley was included, thus
510 bigger initiatives can be projected. Different institutions could be aligned as information
511 contributors. It will reduce the demand for samples when monitoring, especially were resources are
512 limited. To this goal, efforts should be focused in data structuration.

513

514 **5 Conclusions**

515 The opportunistic approach was useful to evaluate the application relevance of the phosphorus
516 fertilization subsidy. The use of both datasets provided an additional insight to the regional
517 situation. By this means, the case study provided evidence that the use of opportunistic data as
518 supplementary information in environmental monitoring is possible and constitutes an alternative
519 for regulation assessment. Data sources are not always tidy and highly reliable, but it does not
520 mean that they should always be discarded. As a low-cost data source, opportunistic data stand
521 out as a convenient add-on in environmental monitoring, especially for developing economies.
522 However, the case study exemplify how entangled the use of third party data can be when soil
523 testing lacks of proper organization.

524

525 **Funding**

526 This work was supported by a conjoint effort of Dirección Regional Metropolitana of the Servicio
527 Agrícola y Ganadero (Agricultural and Livestock Service, Chile); Instituto de Investigaciones
528 Agropecuarias (INIA) [project numbers 502383-08 and 500041-70]; and CONYCIT [grant number
529 72170044].

530

531 **Acknowledgments**

532 First and foremost, we thank all the personnel that through the years has worked in La Platina Soil
533 and Plant Nutrition Laboratory. Also, we sincerely thank the Comité Técnico Regional para la
534 Sustentabilidad Ambiental de los Suelos Degradados (RM), specially to Ivone Aranguiz from
535 Secretaría Ministerial de Agricultura, and Pilar Toledo from Instituto de Desarrollo Agropecuario.
536 Special thanks to all members of the Servicio Agrícola y Ganadero and Instituto de Investigaciones
537 Agropecuarias that contribute with the sampling campaign that made this work possible. We also
538 thank Selamawit Amare, Coleen Carranza, Mirzokhid Mirshadiev, Demie Moore, Ricardo Teixeira
539 da Silva, Yan Wang, and Miao Yu, for proofreading the manuscript.

540

541 **References**

542 Abbott, B.W., Moatar, F., Gauthier, O., Fovet, O., Antoine, V., Ragueneau, O., 2018. Trends and
543 seasonality of river nutrients in agricultural catchments: 18years of weekly citizen science in
544 France. Science of The Total Environment 624, 845-858.
545 <https://doi.org/10.1016/j.scitotenv.2017.12.176>

546 Allen, B.L., Mallarino, A.P., 2006. Relationships between extractable soil phosphorus and
547 phosphorus saturation after long-term fertilizer or manure application. Soil Science Society
548 of America Journal 70(2), 454-463. <https://doi.org/10.2136/sssaj2005.0031>

549 Auerswald, K., Fischer, F.K., Kistler, M., Treisch, M., Maier, H., Brandhuber, R., 2018. Behavior of
550 farmers in regard to erosion by water as reflected by their farming practices. Science of The
551 Total Environment 613-614, 1-9. <https://doi.org/10.1016/j.scitotenv.2017.09.003>

552 Barrett, C.B., Bevis, L.E.M., 2015. The self-reinforcing feedback between low soil fertility and
553 chronic poverty. Nature Geoscience 8(12), 907-912. <https://doi.org/10.1038/ngeo2591>

554 Bivand, R., Keitt, T., Rowlingson, B., 2017. rgdal: Bindings for the 'Geospatial' Data Abstraction
555 Library. R package version 1.2-15.

556 Caro, J.C., Melo, O., Foster, W., 2006. Participación e Impacto del Programa de Recuperación de
557 Suelos Degradados en Usuarios de INDAP. Economía Agrária 10, 11-24.

558 Casanova, M., Salazar, O., Seguel, O., Luzio, W., 2013. The Soils of Chile. World Soils Book
559 Series Springer, Dordrecht, Netherlands. <https://doi.org/10.1007/978-94-007-5949-7>
560 CIREN, 1996. Estudio agrológico Región Metropolitana. Publicación CIREN 115. Centro de
561 Información de Recursos Naturales (CIREN), Santiago, Chile.
562 CONAF, CIREN, 2013. Monitoreo de cambios, corrección cartográfica y actualización del catastro
563 de los recursos vegetacionales nativos de las regiones de Valparaíso, Metropolitana y
564 Libertador Bernardo O'Higgins. Informe Técnico Final. Corporación Nacional Forestal
565 (CONAF), Centro de Información de Recursos Naturales (CIREN), Santiago, Chile.
566 Cowles, M.K., 2013. Applied Bayesian Statistics. Springer Texts in Statistics. Springer, New York,
567 NY. <https://doi.org/10.1007/978-1-4614-5696-4>
568 Daly, K., Styles, D., Lalor, S., Wall, D.P., 2015. Phosphorus sorption, supply potential and
569 availability in soils with contrasting parent material and soil chemical properties. European
570 Journal of Soil Science 66(4), 792-801. <https://doi.org/10.1111/ejss.12260>
571 Diner, D., Nakayama, S., Nov, O., Porfiri, M., 2018. Social signals as design interventions for
572 enhancing citizen science contributions. Information, Communication & Society 21(4), 594-
573 611. <https://doi.org/10.1080/1369118X.2017.1299779>
574 Dirección Meteorológica de Chile, 2010-2016. Anuarios climatológicos. Dirección General de
575 Aeronáutica Civil, Dirección Meteorologica de Chile, Subdepartamento Climatología y
576 Meteorología Aplicada., Santiago, Chile.
577 Dupas, R., Delmas, M., Dorioz, J.M., Garnier, J., Moatar, F., Gascuel-Odoux, C., 2015. Assessing
578 the impact of agricultural pressures on N and P loads and eutrophication risk. Ecological
579 Indicators 48, 396-407. <https://doi.org/10.1016/j.ecolind.2014.08.007>
580 Fischer, P., Pöthig, R., Venohr, M., 2017. The degree of phosphorus saturation of agricultural soils
581 in Germany: Current and future risk of diffuse P loss and implications for soil P
582 management in Europe. Science of the Total Environment 599-600, 1130-1139.
583 <https://doi.org/10.1016/j.scitotenv.2017.03.143>
584 Fiszbein, A., Kanbur, R., Yemtsov, R., 2014. Social Protection and Poverty Reduction: Global
585 Patterns and Some Targets. World Development 61, 167-177.
586 <https://doi.org/10.1016/j.worlddev.2014.04.010>

587 Floress, K., Reimer, A., Thompson, A., Burbach, M., Knutson, C., Prokopy, L., Ribaud, M., Ulrich-
 588 Schad, J., 2018. Measuring farmer conservation behaviors: Challenges and best practices.
 589 Land Use Policy 70, 414-418. <https://doi.org/10.1016/j.landusepol.2017.11.030>
 590 Gelman, A., Carlin, J.B., Stern, H.S., Dunson, D.B., Vehtari, A., Rubin, D.B., 2013. Bayesian Data
 591 Analysis. Chapman & Hall/CRC Texts in Statistical Science. Third Edition ed. CRC Press,
 592 Boca Raton, FL.
 593 Giraud, C., Calenge, C., Coron, C., Julliard, R., 2016. Capitalizing on opportunistic data for
 594 monitoring relative abundances of species. *Biom* 72(2), 649-658.
 595 <https://doi.org/10.1111/biom.12431>
 596 Hijmans, R.J., 2017. raster: Geographic Data Analysis and Modeling. R package version 2.6-7.
 597 Holden, S.T., Lunduka, R.W., 2014. Input subsidies, cash constraints, and timing of input supply.
 598 *American Journal of Agricultural Economics* 96(1), 290-307.
 599 <https://doi.org/10.1093/ajae/aat059>
 600 Kelepertzis, E., 2014. Accumulation of heavy metals in agricultural soils of Mediterranean: Insights
 601 from Argolida basin, Peloponnese, Greece. *Geoderma* 221-222(Supplement C), 82-90.
 602 <https://doi.org/10.1016/j.geoderma.2014.01.007>
 603 Ketterings, Q.M., Czymmek, K.J., 2012. Phosphorus index as a phosphorus awareness tool:
 604 Documented phosphorus use reduction in New York state. *Journal of Environmental*
 605 *Quality* 41(6), 1767-1773. <https://doi.org/10.2134/jeq2012.0050>
 606 Koppmair, S., Kassie, M., Qaim, M., 2017. The influence of farm input subsidies on the adoption of
 607 natural resource management technologies. *Australian Journal of Agricultural and*
 608 *Resource Economics* 61(4), 539-556. <https://doi.org/10.1111/1467-8489.12220>
 609 Kottek, M., Grieser, J., Beck, C., Rudolf, B., Rubel, F., 2006. World Map of the Köppen-Geiger
 610 climate classification updated. *Meteorologische Zeitschrift* 15(3), 259-263.
 611 <https://doi.org/10.1127/0941-2948/2006/0130>
 612 Krueger, T., 2017. Bayesian inference of uncertainty in freshwater quality caused by low-resolution
 613 monitoring. *Water Research* 115, 138-148. <https://doi.org/10.1016/j.watres.2017.02.061>

614 Lima, L.S.d., Krueger, T., García-Marquez, J., 2017. Uncertainties in demonstrating environmental
615 benefits of payments for ecosystem services. *Ecosystem Services* 27, 139-149.
616 <https://doi.org/10.1016/j.ecoser.2017.09.005>

617 Lots, F.A.E., Behrens, P., Vijver, M.G., Horton, A.A., Bosker, T., 2017. A large-scale investigation
618 of microplastic contamination: Abundance and characteristics of microplastics in European
619 beach sediment. *Marine Pollution Bulletin* 123(1), 219-226.
620 <https://doi.org/10.1016/j.marpolbul.2017.08.057>

621 Lowder, S.K., Bertini, R., Croppenstedt, A., 2017. Poverty, social protection and agriculture: Levels
622 and trends in data. *Global Food Security* 15, 94-107.
623 <https://doi.org/10.1016/j.gfs.2017.06.001>

624 Mason, N.M., Jayne, T.S., 2013. Fertiliser subsidies and smallholder commercial fertiliser
625 purchases: Crowding out, leakage and policy implications for Zambia. *Journal of*
626 *Agricultural Economics* 64(3), 558-582. <https://doi.org/10.1111/1477-9552.12025>

627 Mason, N.M., Jayne, T.S., Mofya-Mukuka, R., 2013. Zambia's input subsidy programs. *Agricultural*
628 *Economics* 44(6), 613-628. <https://doi.org/10.1111/agec.12077>

629 Minasny, B., McBratney, A.B., 2006. A conditioned Latin hypercube method for sampling in the
630 presence of ancillary information. *Computers & Geosciences* 32(9), 1378-1388.
631 <https://doi.org/10.1016/j.cageo.2005.12.009>

632 Ministerio de Agricultura, 1999. Decreto con fuerza de ley 235. Establece sistema de incentivos
633 para la recuperacion de suelos degradados. Gobierno de Chile.

634 Ministerio de Agricultura, 2010. Ley número 20.412. Establece un sistema de incentivos para la
635 sustentabilidad agroambiental de los suelos agropecuarios. Gobierno de Chile.

636 Ministerio de Agricultura, 2015. Decreto 51. Fija reglamento de la ley N 20.412 que establece un
637 sistema de incentivos para la sustentabilidad agroambiental de los suelos agropecuarios.
638 Gobierno de Chile.

639 Nyssen, J., Biruk, B., Tesfamariam, Z., Frankl, A., Demissie, B., Ghebreyohannes, T., Meaza, H.,
640 Poesen, J., Van Eetvelde, V., Zenebe, A., Deckers, J., Haile, M., 2017. Geographical
641 determinants of inorganic fertiliser sales and of resale prices in north Ethiopia. *Agriculture,*
642 *Ecosystems & Environment* 249, 256-268. <https://doi.org/10.1016/j.agee.2017.07.037>

643 Olsen, S.R., Cole, C.V., Watanabe, F.S., 1954. Estimation of available phosphorus in soils by
644 extraction with sodium bicarbonate. Circular / United States Department of Agriculture;no.
645 939. USDA, Washington.

646 QGIS Development Team, 2017. QGIS Geographic Information System. Open Source Geospatial
647 Foundation Project.

648 R Core Team, 2017. R: A Language and Environment for Statistical Computing. R Foundation for
649 Statistical Computing, Vienna, Austria.

650 Ribey, M.A., O'Halloran, I.P., 2016. Consequences of Ontario P index recommendations for
651 reduced manure and fertilizer phosphorus applications on corn yields and soil phosphorus.
652 Canadian Journal of Soil Science 96(2), 191-198. <https://doi.org/10.1139/cjss-2015-0072>

653 Ricker-Gilbert, J., Jayne, T.S., 2017. Estimating the Enduring Effects of Fertiliser Subsidies on
654 Commercial Fertiliser Demand and Maize Production: Panel Data Evidence from Malawi.
655 Journal of Agricultural Economics 68(1), 70-97. <https://doi.org/10.1111/1477-9552.12161>

656 Roberts, W.M., Gonzalez-Jimenez, J.L., Doody, D.G., Jordan, P., Daly, K., 2017. Assessing the
657 risk of phosphorus transfer to high ecological status rivers: Integration of nutrient
658 management with soil geochemical and hydrological conditions. Science of the Total
659 Environment 589, 25-35. 10. <https://doi.org/1016/j.scitotenv.2017.02.201>

660 Roudier, P., 2017. clhs: a R package for conditioned Latin hypercube sampling. R package version
661 0.5-7.

662 Roudier, P., Hewitt, A.E., Beaudette, D.E., 2012. A conditioned Latin hypercube sampling
663 algorithm incorporating operational constraints. In: B. Minasny, B.P. Malone, A.B.
664 McBratney (Eds.), Digital Soil Assessments and Beyond. CRC Press, London, UK.

665 Sadzawka, A., Carrasco, M.A., Grez, R., Mora, M.d.I.L., Flores, H., Neaman, A., 2006. Métodos de
666 análisis de suelos recomendados para los suelos de Chile. Revisión 2006. Serie Actas INIA
667 N° 34. Instituto de Investigaciones Agropecuarias, Santiago, Chile.

668 Silvertown, J., 2009. A new dawn for citizen science. Trends in Ecology & Evolution 24(9), 467-
669 471. <https://doi.org/10.1016/j.tree.2009.03.017>

670 Sullivan, T.J., Driscoll, C.T., Beier, C.M., Burtraw, D., Fernandez, I.J., Galloway, J.N., Gay, D.A.,
671 Goodale, C.L., Likens, G.E., Lovett, G.M., Watmough, S.A., 2018. Air pollution success

672 stories in the United States: The value of long-term observations. *Environmental Science*
 673 and Policy 84, 69-73. <https://doi.org/10.1016/j.envsci.2018.02.016>
 674 Tarfasa, S., Balana, B.B., Tefera, T., Woldeamanuel, T., Moges, A., Dinato, M., Black, H., 2018.
 675 Modeling Smallholder Farmers' Preferences for Soil Management Measures: A Case Study
 676 From South Ethiopia. *Ecological Economics* 145, 410-419.
 677 <https://doi.org/10.1016/j.ecolecon.2017.11.027>
 678 The National Aeronautics and Space Administration, N., Ministry of Economy Trade and Industry,
 679 M., 2011. The Advanced Spaceborne Thermal Emission and Reflection Radiometer
 680 (ASTER) Global Digital Elevation Model (GDEM). Version 2. ASTER GDEM is a product of
 681 NASA and METI.
 682 Tirivayi, N., Knowles, M., Davis, B., 2016. The interaction between social protection and
 683 agriculture: A review of evidence. *Global Food Security* 10, 52-62.
 684 <https://doi.org/10.1016/j.gfs.2016.08.004>
 685 Torrent, J., Barberis, E., Gil-Sotres, F., 2007. Agriculture as a source of phosphorus for
 686 eutrophication in southern Europe. *Soil Use and Management* 23(SUPPL. 1), 25-35.
 687 <https://doi.org/10.1111/j.1475-2743.2007.00122.x>
 688 Tulloch, A.I.T., Possingham, H.P., Joseph, L.N., Szabo, J., Martin, T.G., 2013. Realising the full
 689 potential of citizen science monitoring programs. *Biological Conservation* 165, 128-138.
 690 <https://doi.org/10.1016/j.biocon.2013.05.025>
 691 Venables, W., Ripley, B., 2002. *Modern Applied Statistics with S*. Fourth ed. Springer, New York.
 692 <https://doi.org/10.1007/978-0-387-21706-2>
 693 Watson, C.J., Smith, R.V., Matthews, D.I., 2007. Increase in phosphorus losses from grassland in
 694 response to Olsen-P accumulation. *Journal of Environmental Quality* 36(5), 1452-1460.
 695 <https://doi.org/10.2134/jeq2006.0207>
 696 Williams, M.R., King, K.W., Dayton, E., Labarge, G.A., 2015. Sensitivity analysis of the ohio
 697 phosphorus risk index. *Transactions of the ASABE* 58(1), 93-102.
 698 <https://doi.org/10.13031/trans.58.10778>

699 Yu, B., Fan, S., Magalhães, E., 2015. Trends and Composition of Public Expenditures: A Global
700 and Regional Perspective. The European Journal of Development Research 27(3), 353-
701 370. <https://doi.org/10.1057/ejdr.2015.26>

702

703 **Figure Captions**

704 Figure 1. Interactive Map: Chilean Metropolitana Region. Soils comprehended in the study area
705 are marked with light red polygons that include soil order, suborder, great group, and subgroup.
706 Sampling points are indicated, each holding information of land use, P-Olsen, and P-Buffer.

707

708 Figure 2. Histogram of scaled and log-transformed ($\ln$) P-Olsen values in the INIA dataset (a) and
709 the soil monitoring dataset (b). The density of the normal distribution $N(\mu = 0, \sigma^2 = 1)$ is included in
710 red.

711

712 Figure 3. Histogram of bootstrapped values for the mean (μ) (a) and precision (τ) (b) of log-
713 transformed P-Olsen values in INIA dataset. the normal distribution function $N(\mu = 0, \sigma^2 = 1)$ is
714 proposed as a theoretical approximation for μ , and the gamma distribution $Ga(\alpha = 29, \beta = 46)$ for τ .

715

716 Figure 4. Empirical cumulative density function for expected P-Buffer values.

717

718 Figure 5. Spatial distribution for P-Olsen concentrations. North-south and west-east transects
719 regarding soil P-Olsen concentration are included. Block means every 3km are shown by a black
720 line.

721

722 Figure 6. Average cumulative distribution function estimated for P-Olsen within the study area
723 (solid line), including a 95% confidence interval (dotted line).

Program clusters	Conservation/restoration practice
Application of phosphate fertilizers	Phosphate fertilizers
Application of essential chemical elements	Liming Potassium fertilizers Sulfur fertilizers
Establishment of a vegetative cover on bare soils or with deteriorated cover	Sowing or maintenance of grasslands
Use of soil conservation practices	Compost Chicken manure Other manures Guano Phosphate rock No-till sowing Drinking troughs Diversion channels Barbed wire fence Ursus mesh fence Electric fence Countour stone bunds Bench terraces Negarim microcatchments Semi-circular bunds Water spreading bunds Green manure Incorporation of volcanic ashes and oat cultivation (after eruption) Land levelling Use of chisel plow Use of subsoiler
Remotion, cleaning or confinement of physical or chemical impediments	Scrub removal <i>Ulex europaeus</i> L. removal Stone removal
Use of soil conservation practices [whole country]	Narrow buffer strips No-till stubble reduction No-till herbicide application Gully control Windbreaks Agroforestry Exclosure (no grazing) Adjust livestock numbers Stubble management Nitrification inhibitors Crop rotation

Note: The provided information is an independent transcription of the official document (Ministerio de Agricultura, 2015) available at

Note: For a definition of each practice, the supplementary decree of the previous one is available at [Spanish] <http://bcn.cl/28c5p>

[Spanish] <http://bcn.cl/1vg4w>

Order	Suborder	Greatgroup	Subgroup	Area	Samples	Area : Samples
				ha	n	ha/n
Alfisol	Xeralfs	Durixeralfs	Abruptic Durixeralfs	874	1	874
Alfisol	Xeralfs	Haploxeralfs	Mollic Haploxeralfs	3722	7	532
Alfisol	Xeralfs	Haploxeralfs	Ultic Haploxeralfs	20490	19	1078
Entisol	Aquepts	Fluvaquepts	Aeric Fluvaquepts	1335	2	668
Entisol	Orthents	Xerorthents	Typic Xerorthents	3516	9	391
Inceptisol	Aquepts	Epiaquepts	Mollic Epiaquepts	2077	3	692
Inceptisol	Xerepts	Haploxerepts	Fluventic Xerochrept	2413	7	345
Inceptisol	Xerepts	Haploxerepts	Typic Xerochrepts	24183	45	537
Mollisol	Aquolls	Calciaquolls	Petrocalcic Calciaqu	5436	10	544
Mollisol	Aquolls	Calciaquolls	Typic Calciaquolls	4469	9	497
Mollisol	Aquolls	Epiaquolls	Fluvaquentic Epiaquo	2839	3	946
Mollisol	Xerolls	Argixerolls	Typic Argixerolls	6319	9	702
Mollisol	Xerolls	Calcixerolls	Vertic Calcixerolls	2460	4	615
Mollisol	Xerolls	Durixerolls	Vitradic Durixerolls	18086	31	583
Mollisol	Xerolls	Haploxerolls	Calcic Haploxerolls	1574	2	787
Mollisol	Xerolls	Haploxerolls	Duric Haploxerolls	383	2	192
Mollisol	Xerolls	Haploxerolls	Entic Haploxerolls	18446	36	512
Mollisol	Xerolls	Haploxerolls	Fluventic Haploxerol	40823	77	530
Mollisol	Xerolls	Haploxerolls	Lithic Haploxerolls	1850	2	925
Mollisol	Xerolls	Haploxerolls	Pachic Haploxerolls	1139	4	285
Mollisol	Xerolls	Haploxerolls	Typic Haploxerolls	21234	50	425
Mollisol	Xerolls	Haploxerolls	Ultic Haploxerolls	20290	39	520
Mollisol	Xerolls	Haploxerolls	Vertic Haploxerolls	8120	16	508
Mollisol	Xerolls	Palexerolls	Haplic Palexerolls	1171	3	390
Mollisol	Xerolls	Palexerolls	Petrocalcic Palexero	2250	3	750
Mollisol	Xerolls	Palexerolls	Vertic Palexerolls	2107	6	351
Vertisol	Aquerts	Epiaquerts	Halic Epiaquerts	1062	1	1062
Vertisol	Xererts	Haploxerts	Sodic Haploxererts	4078	7	583
Vertisol	Xererts	Haploxerts	Typic Haploxererts	4590	6	765
Recent terraces or unconsolidated sediments				-	71	-
Total				227336	484