SMART SAMPLING TO ASSIST ON-FARM NUTRIENT MANAGEMENT

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Abstract
On-farm accurate and efficient use of nutrients requires advanced decision support tools for assigning application rates and timing. In many cases nutrient application should be varied spatially, due to local variations in soil fertility. Therefore soil testing positions should be selected to sample the likely variation, which will be due to soil and topographic features, as well as management history. This paper presents a method to select the sampling positions to take soil cores for standard soil fertility testing, with respect to the soil and topographic variations encountered. This is enabled by the collection of high resolution proximally sensed data, such as that collected by an electromagnetic (EM) survey. In this paper we present flat land (Massey University dairy farm) and hill country (Pohangina pastoral farm) case study examples because our method of selection changes for difficult, inaccessible country in comparison to easily accessible flat land. The method selects sampling positions with a statistical distribution matching the statistical distribution of the whole area. Digital information used to conduct this analysis, for this study, includes the co-variate datalayers: soil electrical conductivity (to 1 m), slope, elevation and a wetness index.

Introduction
Soil scientists now have access to a large variety of detailed, digital information that can assist with planning a sampling campaign. In New Zealand, land information is available from the LRIS portal[1], for example a country-wide digital elevation map (25-m resolution). Additional resources are also listed on the National Land Resource Centre website[2]. Also site-specific sensor surveys can be conducted using on-the-go systems, such as EM (electromagnetic) surveys which collect high resolution sensor data reflecting soil texture and moisture differences (Hedley et al., 2004).

Environmental covariates such as land cover, slope, soil maps, and EM survey data are proxies for soil-forming factors (Jenny, 1941). The conditioned Latin hypercube sampling (cLHS) method, proposed by Minasny and McBratney (2006), provides soil scientists with a robust sample allocation tool which uses a stack of land information datalayers to derive a "stratified sampling strategy".

Method

Case study sites
The Massey No.1 Dairy Unit was selected to represent an accessible, flat land farm, and a farm in the Pohangina Valley, was selected to represent a hill country farm, with some very inaccessible areas.

[1] http://lris.scinfo.org.nz
[2]http://www.nlrc.org.nz/resources/datasets

Sampling based on environmental covariates in easily accessible country

The cLHS method has been applied to select twenty soil sampling positions at our flat land research site (Massey University Dairy No1 Unit) using an EM survey and terrain attributes derived from a high-resolution digital elevation map (DEM) (elevation, slope, SAGA Wetness Index). Elevation and slope are primary terrain attributes derived from the DEM. The SAGA Wetness Index is a secondary terrain attribute derived from slope, elevation and profile curvature (Boehner et al., 2002). The sampling positions proposed by the analysis are shown in Figure 1. Results indicate that the statistical distributions of the sampled set, matches with the original statistical distributions of the environmental covariates (Figure 2). The analysis was conducted using the R statistical environment (R Core Team, 2013).

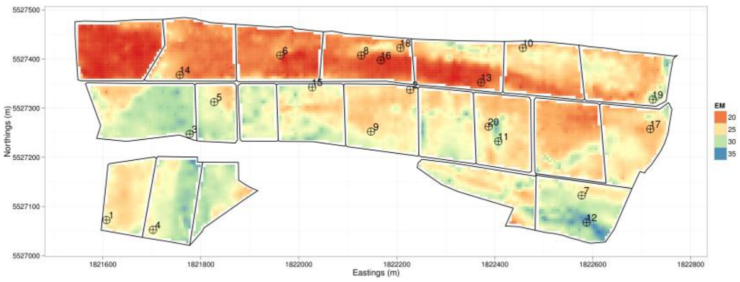

Figure 1: Twenty sampling locations selected by the cLHS algorithm based on EM, elevation, slope and SAGA Wetness Index.

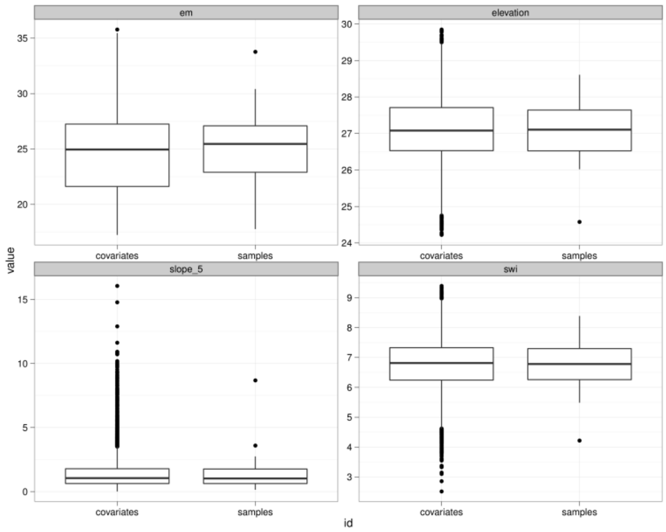

Figure 2 Comparison of the statistical distributions of the environmental covariates in the original GIS layers and in the 20 selected sampling locations.

Sampling in a constrained environment

In rough terrain or remote regions, sampling efficiency is affected by accessibility, i.e. slope, land cover, and distance from road/trail networks. GIS processing can combine these variables to define the "ease of reach"' of each point in the landscape from the road network (Figure 3). The inclusion of this information allows for the sampling locations to be closer to the road network, making them easier to reach for the soil scientist (Roudier *et al.*, 2012 ; Figures 4, 5).

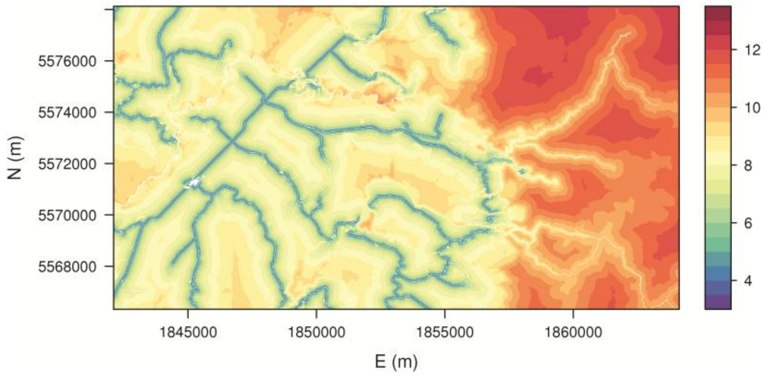

Figure 3 The "cost of reach" layer generated in the GRASS GIS environment from landcover and DEM data.

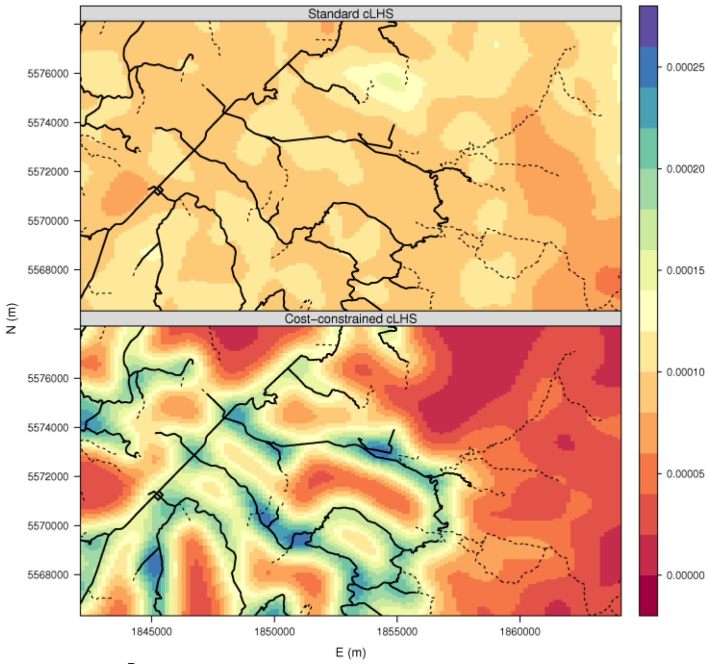

Figure 4 Density (samples/m^2) of the samples locations over 100 realisations of standard and cost-constrained cLHS for a number of samples n = 250 for a dataset in the Pohangina Valley.

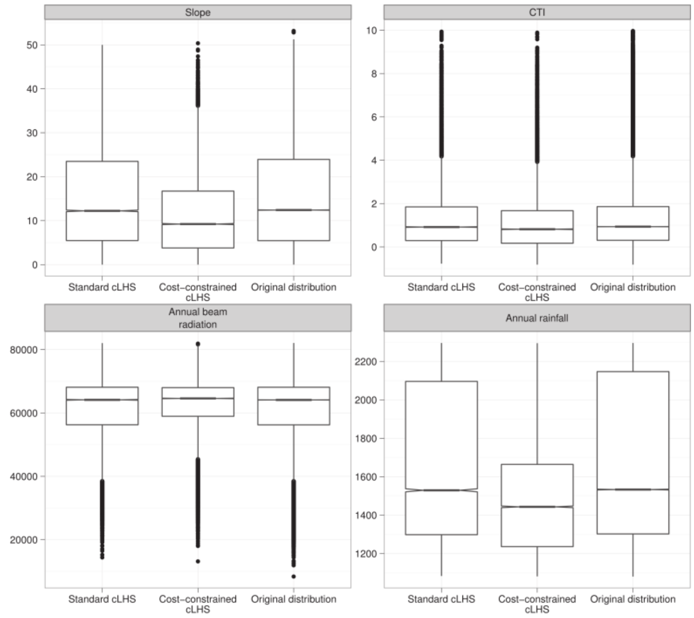

Figure 5 Comparison of the sampling locations given by the standard cLHS implementation (red triangles) and the cost-constrained cLHS implementation (blue dots) plotted over a shaded relief map.

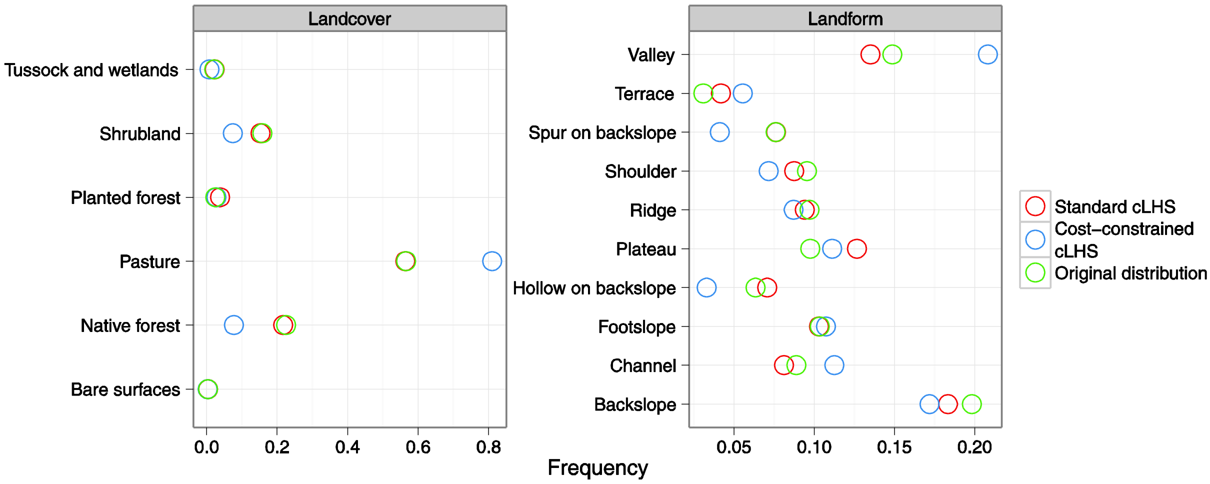

Figure 6 Comparison of the statistical distributions of the environmental covariates in the original GIS layers, in the 250 sampling locations generated by the original cLHS algorithm and in the cost-constrained implementation.

Results on continuous variables show that the features that occur in difficult terrain (mainly slope and rainfall) are under-sampled by the cost-constrained algorithm, because these features are naturally heavily penalised by the cost layer (Figures 5 and 6). The results on landcover and landform elements repartition present a similar trend. This is another illustration of what is done if the cost-constrained method is chosen: unlike the standard algorithm, the Latin hypercube condition cannot be as optimised, but the cost of the produced sampling scheme is reduced so that it can be actually implemented.

Conclusions

The cLHS method has been adopted by the digital soil mapping community, and is suitable in the context of precision agriculture. Additionally, a method to add operational constraints to the standard method has been proposed to address the challenges of sampling in rugged terrain.

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