METHOD TO OPTIMIZE SOIL SURVEY FOR MULTIPLE SOIL PROPERTY

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A paper from the Proceedings of the
16th International Conference on Precision Agriculture
21-24 July 2024
Manhattan, Kansas, United States

Abstract.

The sugarcane production system in Colombia, spanning an area of 241,000 hectares in the geographical valley of the Cauca River, is recognized worldwide due to its high productivity, adoption of advanced technologies, and sustainable management. The natural soil and climate conditions in this region result in significant variability in the chemical and physical soil properties. Consequently, determining the soil variability is crucial to achieving its maximum productive potential through differentiated sustainable management. This research aimed to identify the spatial variability of multiple soil properties thought the development of a method to optimize a sampling pattern called OPMSSA (Optimal Pattern of Multiscale Soil Sampling using Simulated Annealing). The main objective of this methodology is to generate an accurate map of soil sampling points to produce layers that show soil variability. These layers could be used for variable-rate fertilization, achieving a significant reduction in sampling point number compared to conventional methods. This approach leads to cost reduction, decreased application of chemical inputs, and increased efficiency during the sampling process. The OPMSSA method was validated with previous data. Subsequently, it was implemented, and evaluated in a survey for chemical and physical properties in the central zone of the Providencia Sugar Mill. To validate, three sampling patterns (grid, random, and OPMSSA method) were compared in seven blocks with soil chemical properties sampling points. The results showed that the sampling pattern obtained from the OPMSSA method reduced the number of sampling points by up to 40%, compared to the other two evaluated sampling patterns. In conclusion, simulations with the seven blocks demonstrated better performance of the OPMSSA method than grid and random sampling patterns. This finding was verified using bifactorial analysis of variance with a 95% reliability, revealing non-significative differences between the sampling patterns. Consequently, these results confirmed that an analysis of multiple soil properties using the same sampling pattern, might be optimal for one property but suboptimal for others in terms of spatial variability identification.

Keywords.
sampling pattern, optimization, soil properties, OPMSSA, variability

The authors are solely responsible for the content of this paper, which is not a refereed publication. This work should be cited as: Perdomo, D. F. & Sandoval, D. F. (2024). Method to optimize soil survey for multiple soil property. In Proceedings of the 16th International Conference on Precision Agriculture (unpaginated, online). Monticello, IL: International Society of Precision Agriculture.

INTRODUCTION

As we know, the productivity of an agricultural crop will depend on several factors: climate, soil, management practices, and plant physiology, with soil being one of the most important due to changes in its properties by natural and anthropogenic processes (Morell & Hernández, 2008). These changes, which are of a spatiotemporal nature, largely explain the variability in crop productivity, making its study indispensable. For this reason, precision agriculture emerges as a set of technologies and methodologies that allow describing and analyzing the spatial and temporal component of this variability, studying the phenomena present in the soil in greater detail through tools such as geostatistics (Bongiovanni, Mantovani, Best, & Roel, 2006).

The determination of soil properties starts with soil sampling in the field, followed by data processing, to finally generate spatial variability maps of the soil (SVMS) using geostatistics (Sankar, Kumar, & Chattopadhyay, 2018). The most well-known soil sampling patterns (such as systematic grid, random, triangular, etc.) are not applicable in soil science, as they assume independence between sampling points (Brus, 2018). Consequently, these could generate a spatial distribution of sampling points in the field that does not correspond to variability, placing many points in areas where variability is low or few where it is high, thus losing important characteristics of soil spatial variability (Stumpf et al., 2017).

To solve this problem, methods such as two-phase sampling have been developed, which optimize the sampling pattern by dividing it into two distinct stages: In the first phase, a fraction of the total soil samples is taken to identify the spatial behavior of the variables through the calculation of the theoretical semivariogram parameters; in the second phase, the data and semivariogram obtained from the first phase are used as input variables to a prediction algorithm based on heuristic optimization called Spatial Simulated Annealing (SSA); used in various studies of soil spatial variability (Van Groenigen, Siderius, & Stein, 1999; Van Groenigen, 2000).

The SSA algorithm generates additional soil sampling points to those from the initial phase, based on the data provided in the first phase, using the semivariogram as an analysis tool and the minimization of the Kriging Variance function as an optimization criterion (Van Groenigen, 2000). SSA prevents the optimal sampling pattern from converging to a local minimum of the Kriging Variance function by generating perturbations (moving the sampling pattern points to determined distances) and accepting worse solutions with a range of probability set by the user, thus achieving the solution closest to the global optimum (Van Groenigen et al., 1999).

The advantages of this method are the reduction of SVMS errors and the reduction of the number of samples extracted in the field, which lowers the sampling cost and makes it feasible to sample soil properties more frequently. Additionally, this method considers some sampling constraints such as limiting the number of observations and identifying inaccessible areas, among others (Szatmári, László, Takács, Szabó, & Koós, 2018). Furthermore, it allows using data from previous spatial variability analyses, which serve as a basis for optimization, without the need for sampling in the first phase (Simbahan & Dobermann, 2006).

Current spatial sampling patterns do not have a distribution that can identify the variability of multiple soil properties at the same time, resulting in increased costs, extraction time, and sample analysis in the laboratory. Also, SVMS may not present an acceptable error, which would cause a series of poor agronomic decisions leading to economic losses (Szatmári et al., 2018).

The objective of this research was to develop a method to optimize the spatial sampling pattern of multiple soil properties in a single sampling campaign. The proposed method used the SSA algorithm in conjunction with geostatistical techniques.

MATERIALS AND METHODS

SSA Algorithm Parameters

The design of the method began by constructing an algorithm based on SSA to optimize sampling patterns of multiple variables using the R programming language v.3.6.1 (R Core Team, 2019). From the R package spsann, designed by Samuel-Rosa, Brus, & Lark (2017) to optimize sampling patterns for a single variable, the function *optimMKV* was used, which optimizes the sampling pattern to obtain spatial interpolations with low errors. The minimization criterion was applied to the kriging variance function. This is the code snippet used in the method:

```
> optimMKV (points, candi, covars, eqn = z ~ 1, vgm, krige.stat = "mean", ..., schedule = scheduleSPSANN (), plotit = FALSE, track = FALSE, boundary, progress = "txt", verbose = FALSE)
```

```
> objMKV (points, candi, covars, eqn = z ~ 1, vgm, krige.stat = "mean", ...)
```

Where points is a list variable in R that contains the sampled points from the first phase and the number of additional points to optimize; *candi* is a table with the coordinates of candidate locations for the perturbations generated in each iteration of the optimization. Covars is a table with information on the covariables that influence the spatial variability of the study variable, which is optional. The eqn parameter defines the type of kriging; for this work, it was set to 1, representing ordinary kriging; vgm is the theoretical semivariogram model of each variable (for R software, it must be a variogramModel type variable). Krige.stat represents the function to be minimized, with optimMKV having two options: the mean or maximum kriging variance ("mean" - "max."). *Plotit* is optional and is used to visualize the movement of perturbations on a 2D plane. The *Boundary* parameter (polygon that circumscribes the sampling points) can be provided and is recommended as it delimits the study area; if not provided by the user, it is estimated from Candi. Finally, *progress and verbose* are optional and are used to observe the progress percentage of the algorithm execution.

Additionally, *scheduleSPSANN* is a list of 11 control parameters for the SSA algorithm. Below is the code and the default values for each parameter:

```
> scheduleSPSANN (initial.acceptance = 0.95, initial.temperature = 0.001, temperature.decrease = 0.95, chains = 500, chain.length = 1, stopping = 10, x.max, x.min = 0, y.max, y.min = 0, cellsize)
```

Initial.acceptance is a value between 0 and 1 that defines the initial acceptance probability, i.e., the number of patterns that will be accepted in the first *Markov chain*.The *initial.temperature* parameter is a numeric value greater than zero that defines the initial t value of the algorithm. A low temperature value combined with low initial acceptance selects the best patterns in the iterative process of the algorithm (Díaz & Dowsland, 2003).

Temperature.decrease varies between 0 and 1 and is used as a multiplication factor to decrease t in each *Markov chain*. Chains is the maximum number of perturbations where t remains constant. The *chain.length* is the number of *Markov chains*. Stopping is the maximum number of iterations the algorithm accepts without improving the objective function.

Finally, the parameters *x.max, x.min, y.max, y.min* define the minimum and maximum perturbation distance added to each point, and *cellsize* is the horizontal and vertical spacing between the candidate locations of *candi*, with the default value being 0, indicating a finite set of candidate locations. It is important that the x, y coordinates are in a flat coordinate system.

Design of the Multivariate Sampling Pattern Optimization Method with SSA (OPMSSA)

The designed method consists of a series of steps presented in the flowchart in Figure 7. In the initial phase, the structural analysis of soil properties can be obtained in two ways: first, with existing data on the variables in the study area (previous soil samplings, satellite images, previous studies by other entities, etc.). The second way is from a sampling pattern designed with conventional sampling methods combined with some design criteria mentioned in Figure 7.

The assignment of points to optimize for each soil property depends on the range calculated in the theoretical semivariogram. The soil property with the smallest range is always assigned the largest number of points to optimize, and in this way, for the rest of the properties, the smaller the range, the fewer points to optimize.

Multivariate SSA Algorithm

The proposed algorithm consists of a for loop where each property is optimized separately using the *optimMKV* function from the spsann package of R software. The properties are previously classified according to their variability, and depending on this, the number of points to optimize is assigned. The property with the smallest range calculated with the semivariogram is optimized first, assigning it a high-density number of candidate locations *(candi)* distributed throughout the study area. The resulting optimal pattern of the dominant property is the new *candi* for the rest of the properties.

At the end of the optimization cycle, the nearest spatial neighbor of the dominant property for each optimized point is sought from the rest of the properties, and the X and Y coordinates are averaged (using the Fast k-nearest neighbor algorithm). The product is a table with the coordinates and properties to be sampled at each point. It also outputs the optimized resulting patterns per property and the final optimized pattern on a 2D plane, along with the graphs of the objective function behavior during the process.

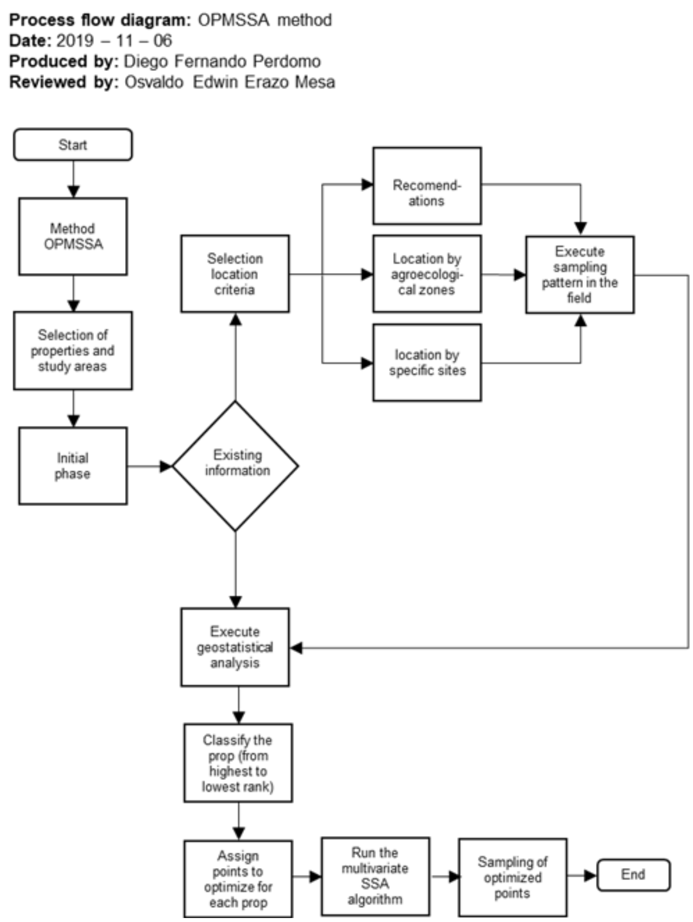

Figure 7. Flowchart of the sampling optimization method using the SSA algorithm.

Validation of the OPMSSA Method with Secondary Data

The validation of the OPMSSA method was conducted using a dataset from Providencia sugar mill factory, which includes soil chemical properties determined in 2014, using a 60m-by-60m grid sampling. This sampling was taken in the central area of the sugar mill, near the village of Amaime (Palmira) and the municipality of Cerrito. The aim of this validation was to reduce the number of sampling points using the method while maintaining similar or lower MEVCs compared to those obtained from random and grid sampling patterns. pH, organic matter (OM), cation exchange capacity (CEC), and apparent electrical conductivity (ECa) were randomly selected for validation. The random selection was made to verify that the method works for any soil property.

The study area for validation covers an area of 282 hectares, which was divided into seven blocks (Figure 8). It was ensured that the plots (the minimum agricultural management area for the sugar mill (see Figure 8) in each block were contiguous and had an average of 100 sampling points. Then, a geostatistical analysis was performed, and each property was interpolated using Ordinary Kriging with the sampling points contained in each block. The resulting interpolations were established as the "real" surface of the selected soil properties. These served as the basis for comparing the three types of sampling patterns: grid, random, and the OPMSSA method.

For the grid and random patterns, 100 sampling points were selected. The values of each soil property at these locations were extracted from the aforementioned "real" surface; with this data, the semivariogram analysis and the interpolation process were performed, and their respective MEVCs were calculated. Subsequently, the steps described in Figure 7 were followed, where for the initial phase of the OPMSSA method, 40 sampling points were randomly selected, and the values of these points were extracted from the "real" surface for semivariogram analysis. Interactively, the minimum number of samples for each property was found, which optimized with the SSA algorithm, gave MEVC values lower or similar to those obtained from the grid and random sampling patterns. This process was carried out in each block.

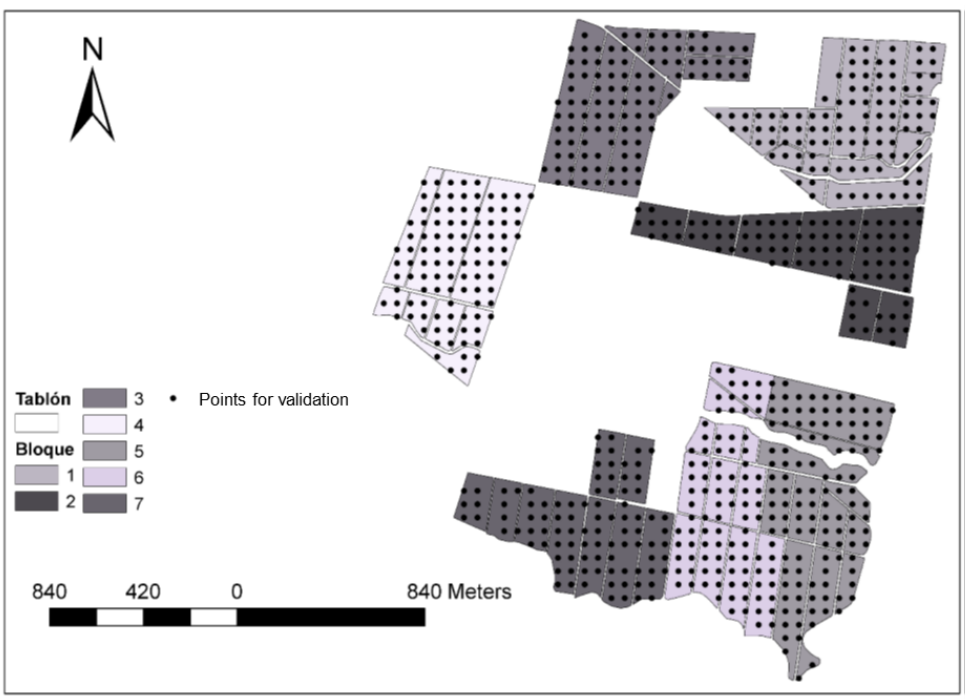

Figure 8. Distribution of the blocks for validation of the OPMSSA method.

The geostatistical analysis was performed using an R script designed to select the best-fit semivariogram model for each property based on the RMSE. Four candidate semivariogram models were chosen, as they are considered the best fit for soil properties according to Lianheng et al. (2018b).

ANOVA for Validating the OPMSSA Method

The experimental design involved a two-factor analysis of variance (ANOVA II) to examine the effects of the soil property and sampling pattern. This method proposes dividing subjects into homogeneous subgroups or blocks and making comparisons among the blocks. In this study, the ANOVA was used to test whether the sampling patterns had an effect on the prediction error of the spatial interpolation, while the soil property did not.

Values for the SSA Algorithm for OPMSSA Method Validation

The parameter values for the SSA algorithm used for validation were selected after a literature review and are as follows:

initial.acceptance = 0.5

initial.temperature = 1000

temperature.decrease = 0.95

chains = 500

chain.length = 1

stopping = 80

x.max = 500

x.min = 0

y.max = 500

y.min = 0

cellsize = 60

Validation of the OPMSSA Method with Field Data

Following the validation of the OPMSSA method with secondary data, field sampling was conducted in the San Jerónimo, El Alizal, Santa Lucía, Samaria, La Esmeralda, Chontaduro, and La Inmaculada Concepción estates. These are located in the central area of Providencia sugar mill near the Amaime district (Palmira) (Figure 9), between coordinates 3° 36' 12" and 3° 38' 39" North latitude and -76° 21' 53" to -76° 16' 26" West longitude, covering an area of approximately 2327 hectares. This region has a tropical climate with an average annual rainfall of 1080 mm and an average annual temperature of 24 °C (IUCN, 2016).

The soils in the study area exhibit a wide variability of soil consociations, describing a cartographic unit dominated by specific physical soil characteristics. This variability includes soil orders such as Mollisols, Vertisols, Inceptisols, and Entisols. These soils are rich in organic matter due to their location in the warm areas of the Cauca River Valley. The soils have good fertility, high clay content, and an abundance of cations and nutrient salts. They exhibit a range of textural phases from moderately fine to coarse and have low slopes of less than 3% (CENICAÑA, 2013).

First Phase of the OPMSSA Method for Physical Properties

In the first phase, the content of clay (Ar), silt (L), and sand (A), bulk density (DA), field capacity moisture [cc], and permanent wilting point moisture [pmp] were determined. From some of these properties, the rapidly available water content (LARA) was calculated for each point. The first phase of the OPMSSA method used existing information from a 2017 survey conducted in the central area of Providencia sugar mill, consisting of 52 points (Figure 9). The criteria for locating these points considered soil consociations, recommendations from the estate managers, and specific zones such as areas with high water tables or sandy regions.

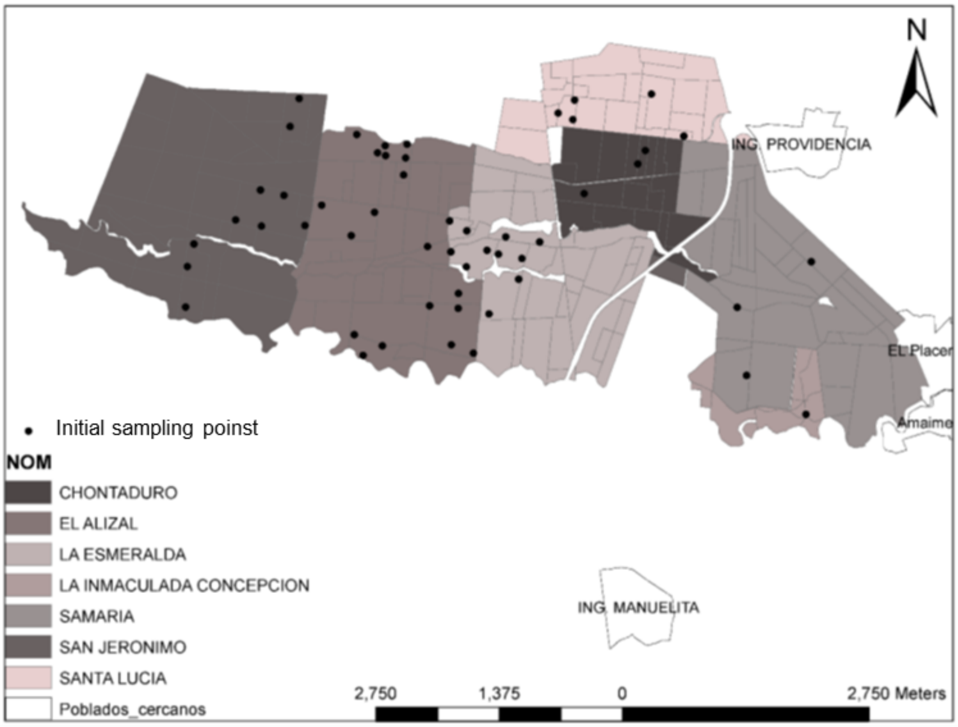

Figure 9. Estates for Sampling Execution and Initial Phase Points.

Optimized Sampling Pattern with the OPMSSA Method (Second Phase)

The steps described in Figure 7 were followed, starting with the geostatistical analysis for each property using data obtained from the initial sampling pattern (Figure 9). Based on the semivariogram analysis, the SSA algorithm was executed, setting the maximum number of points to be optimized (30 points for the dominant property) due to cost, time, and operational constraints. With the locations of the optimized points determined, field sampling was conducted, and laboratory values were determined. These values were then used for semivariogram analysis with all points (initial and optimized), interpolation, and calculation of MEVC.

The parameter values of the SSA algorithm used for optimizing the field sampling pattern of physical properties were:

initial.acceptance = 0.5

initial.temperature = 1000

temperature.decrease = 0.95

chains = 500

chain.length = 2

stopping = 80

x.max = 5000

x.min = 0

y.max = 5000

y.min = 0

cellsize = 1000

Since *x.max, x.min, y.max, y.min*, and *cellsize* values are distances, they should be proportional to the study area. In other words, if the area is large, the distances are recommended to be greater, and vice versa. Hence the difference in values compared to those selected in the validation.

Laboratory Determination Methods for Physical Properties

The laboratory methodology followed was that proposed by IGAC (2006).

RESULTS AND DISCUSSION

Validation of the OPMSSA Method with Secondary Data

Below are the results obtained from the SSA algorithm implemented in the OPMSSA method (times, factors influencing the result, etc.), along with the validation results for Block 1. This block is presented as a summary because the results achieved in the other blocks were similar.

Validation of the OPMSSA Method in Block 1

To validate the OPMSSA method, a random sampling pattern was used as the initial phase, and the property values were extracted from the "real" surface. The semivariogram analysis used to classify the properties from the smallest to the largest range is presented in Table 1. For Block 1, the dominant property was the CIC, which has the smallest range of 314.36 meters.

Table 1. Parameters of the theoretical semivariogram of the initial phase for the OPMSSA method

Property	Sill	Nugget	Range	Model
pH	0.04	0.00	857.96	Spherical
OM	0.76	0.00	1123.95	Gaussian
CIC	4.61	0.06	314.36	Gaussian
ECa	0.04	0.00	7538.74	Spherical

Subsequently, the SSA algorithm was executed with the proposed parameters from the section "Values to use in the SSA algorithm for the validation of the OPMSSA method" and the semivariogram parameters obtained in Table 1, yielding the following results.

Comparison of MEVCs in interpolations for the three sampling patterns and variability maps

After optimizing the patterns for each property with the SSA algorithm and extracting the values from the "real" surface for each property for the grid and random sampling patterns, the semivariogram analysis was performed, and the parameters presented in Table 2 were obtained.

Where the properties in the three patterns presented values of 1.00 in the C/(C0+C) ratio, indicating a strong spatial dependence (Cambardella et al., 2010). There is also a similarity in the semivariogram parameters between the method's patterns and the grid pattern, with the same model for each property.

Table 2. Parameters of the theoretical semivariogram by sampling pattern for each soil property (after optimization with SSA).

Sampling pattern	Property	Sill	Nugget	Range	RMSE	Model	C/(C0+C)
OPMSSA Method	pH	0.03	0.00	983.53	0.00	Spherical	1.00
	OM	0.29	0.00	621.00	0.02	Gaussian	1.00
	CIC	5.29	0.00	283.27	0.77	Gaussian	1.00
	ECa	0.04	0.00	8145.84	0.00	Spherical	1.00
Random	pH	0.39	0.00	8976.79	0.00	Spherical	1.00
	OM	0.13	0.00	389.85	0.02	Gaussian	0.99
	CIC	4.42	0.00	640.62	0.99	Gaussian	1.00
	ECa	0.01	0.00	763.04	0.00	Spherical	0.99
Grid	pH	0.84	0.00	22907.37	0.00	Spherical	1.00
	OM	0.22	0.00	493.32	0.02	Gaussian	0.99
	CIC	5.00	0.03	269.90	0.69	Gaussian	0.99
	ECa	0.04	0.00	6762.99	0.00	Spherical	1.00

Table 3 shows the values of the cross-validation evaluation measures (MEVC) for Block 1. It was observed that pH and ECa had the same RMSE and MAE for each sampling pattern, with the difference that the OPMSSA method reduced the number of sampling points by 44 and 52 compared to the grid and random patterns. OM and CEC had insignificant differences between patterns, with a reduction of 50 and 40 sampling points, respectively. The explained variability for all properties ranged between 50% and 75% for all sampling patterns. These RMSEr values represent the explained variability (Arrouays et al., 2014).

An inverse relationship between the RMSEr value and the R value is also observed (Table 3). For example, the ECa property with an average RMSEr of 84% for each sampling pattern had low R values, averaging 0.50. In contrast, the pH property, which had low RMSEr values, obtained the highest R (averaging 0.75) among the three patterns.

Table 3. Cross-validation results and statistical summary of the interpolations.

Sampling pattern	Property	RMSE	RMSEr	MAE	R	Maximum	Minimum	Mean	STD	No. Points*
OPMSSA Method	pH	0.17	65.15	0.13	0.74	7.53	6.98	7.25	0.14	56
	OM	0.44	73.95	0.35	0.68	3.52	2.07	2.51	0.29	50
	CIC	3.91	78.89	2.99	0.64	25.41	16.99	20.93	1.85	60
	ECa	0.12	83.90	0.07	0.51	0.48	0.29	0.38	0.05	48
Random	pH	0.17	66.69	0.13	0.75	7.54	6.96	7.25	0.15	100
	OM	0.46	76.65	0.35	0.67	3.38	2.07	2.49	0.28	100
	CIC	4.00	80.52	2.98	0.64	25.27	17.23	20.88	1.80	100
	ECa	0.12	85.24	0.07	0.54	0.50	0.28	0.38	0.05	100
Grid	pH	0.17	65.76	0.13	0.76	7.52	6.96	7.25	0.15	100
	OM	0.44	73.88	0.34	0.70	3.54	2.07	2.49	0.30	100
	CIC	3.95	79.41	2.95	0.66	25.42	17.03	20.91	1.85	100
	ECa	0.12	84.38	0.07	0.56	0.50	0.28	0.38	0.05	100

*Number of Sampling Points Used to Interpolate the Analyzed Soil Properties

Table 4 contains the results obtained from the two-factor analysis of variance. The factors: the pattern and the property were significant independently, while the interaction between pattern and property had no effect on the response variable (in this case, the MEVC). For the purposes of this thesis, there were no significant differences between the evaluated patterns, meaning that the same quality of MVES is obtained whether sampling with a grid or random pattern of 100 points or with the OPMSSA method, which reduced the number of these 100 sampling points by an average of 40%.

Table 4. Results of the two-way analysis of variance (evaluation of assumptions).

	Df	Sum Sq	Mean Sq	F Value	Pr (>F)
Pattern	2	925	462.70	3.26	0.04*
Property	3	2802	933.80	6.57	0.00**
Pattern : Property	6	106	17.70	0.12	0.99
Residuals	72	10230	142.10		

*Significant values p < .05; **Very significant values p < .01; ***Highly significant* values p < .001

General Results Found from the OPMSSA Method Validation with the Seven Blocks

In section "Validation of the OPMSSA Method with Secondary Data", only the results obtained from block 1 were shown, because the results found in the remaining six blocks were repetitive. This was verified through bifactorial analysis of variance (described in section ANOVA for Validating the OPMSSA Method) executed to compare the three evaluated patterns, based on the MEVC obtained from the interpolations corresponding to these patterns. The results indicated that there were no significant differences between patterns with a reliability level of 95%. On the other hand, significant differences were found between properties because they present different numerical scales, but this does not affect the error associated with interpolation.

Table 5 presents the percentages of reduction in sampling points generated by the OPMSSA method, where a reduction between 40% and 56% is observed compared to grid and random sampling patterns. This represents progress for agriculture in terms of periodic soil property analysis, within a framework constrained by budget and MVES precision. For example, in the case of Providencia sugar mill, which sampled 3770 points on a grid for chemical property analysis, with a cost of USD$ 79,776. With the implementation of the SSA method, savings of USD$ 31,914 could be generated for the second round of chemical analysis, not counting the precision that could be achieved in fertilization recommendations.

Table 5. Percentage reductions in sampling points with the OPMSSA method pattern versus random and grid patterns.

Property	Block 1	Block 2	Block 3	Block 4	Block 5	Block 6	Block 7
pH	44%	50%	55%	51%	40%	40%	40%
OM	50%	54%	40%	40%	43%	46%	47%
ECa	52%	46%	43%	54%	52%	52%	47%
CIC	40%	40%	54%	50%	45%	46%	56%

Conclusion or Summary

It has been demonstrated that the proposed OPMSSA method in this undergraduate thesis document merges optimized soil property sampling patterns into one, allowing for obtaining MVES with low errors for all properties. The total number of points to sample from the resulting pattern is not equal for all properties, which reduces the number of points to sample by up to 50%. Ultimately, this translates into cost savings in sampling, both in field surveying and in the time and reagents used in the laboratory.

Simulations conducted with the seven blocks showed better performance of the OPMSSA method compared to grid and random sampling patterns. This was verified with a bifactorial analysis of variance that yielded a reliability of 95%, with minor differences between sampling patterns. As a result of these findings, it was confirmed that when conducting an analysis of multiple properties with the same sampling pattern, it may be optimal for one property but suboptimal for others, in terms of identifying spatial variability.

The application of the OPMSSA method in real sampling yielded results consistent with reality, with relatively low MEVC compared to other similar studies and correlations of the analyzed physical properties according to theory.

It was found that the parameters of the semivariogram influence the optimization of the pattern with the SSA algorithm. Additionally, the SSA algorithm can be designed with various objective functions according to the sampling needs. In conclusion, the OPMSSA method can be used by small, medium, and large-scale farmers with or without existing information on variability.

Acknowledgments

I am grateful first to God, and then I deeply thank my mother for her unwavering support throughout my career, to my aunt María Luisa for her advice and constant help, to my sister, and to my entire family. All of you were part of this process and were a pillar of love and hope in difficult times.

I thank Professor Edwin Erazo for his guidance and constant support during this academic process and throughout the execution of this work. To Engineer Diego Sandoval for giving me the opportunity to join his work group at sugar mill Providencia and to all the collaborators of the mill who made it possible with their actions to conclude this undergraduate thesis.

References

Arrouays;, D., McKenzie;, N., JonHempel;, Forges;, A. R. de, & McBrantney, A. (2014). GlobalSoilMap: Basis of the Global Spatial Soil Information System - Proceedings of the 1st GlobalSoilMap Conference. GlobalSoilMap: Basis of the Global Spatial Soil Information System - Proceedings of the 1st GlobalSoilMap Conference. Retrieved from https://books.google.com.co/books?id=3OPKBQAAQBAJ&pg=PA370&dq=Mean+square+error+normalized+by+standard+deviation+soil+maps&hl=es-419&sa=X&ved=0ahUKEwjwq6L-96bmAhWLxFkKHYGnDLwQ6AEIMjAB#v=onepage&q=Mean square error normalized by standard deviation soil map

Bongiovanni, R., Chartuni Mantovani, E., Best, S., & Roel, Á. (2006). Agricultura de Presición: Integando Conocimentos para una Agricultura Moderna y Sustentable.

Brus, D. J. (2018). Geoderma Sampling for digital soil mapping: A tutorial supported by R scripts. *Geoderma*, (July), 0–1. https://doi.org/10.1016/j.geoderma.2018.07.036

Cambardella, C. A., Moorman, T. B., Parkin, T. B., Karlen, D. L., Novak, J. M., Turco, R. F., & Konopka, A. E. (2010). Field-Scale Variability of Soil Properties in Central Iowa Soils. Soil Science Society of America Journal, 58(5), 1501. https://doi.org/10.2136/sssaj1994.03615995005800050033x

Díaz, B. A., & Dowsland, K. A. (2003). Diseño de Heurística y Fundamentos del Recocido Simulado. Inteligencia Artificial. Revista Iberoamericana de Inteligencia Artificial, 7(19). Retrieved from http://www.redalyc.org/resumen.oa?id=92571906

Lianheng, Z., Shuaihao, Z., Dongliang, H., Shi, Z., & Dejian, L. (2018). Quantitative characterization of joint roughness based on semivariogram parameters. International Journal of Rock Mechanics and Mining Sciences, 109(June), 1–8. https://doi.org/10.1016/j.ijrmms.2018.06.008

Morell, F., & Hernández, D. L. A. (2008). Finca la rosita. ii: factores limitantes de los suelos, 29(2), 17–20.

RStudio Team (2019). RStudio: Integrated Development for R. RStudio, Inc., Boston, MA URL http://www.rstudio.com/.

Samuel-rosa, A. A., Brus, D., & Lark, M. (2017). Package ‘ spsann .’

Simbahan, G. C., & Dobermann, A. (2006). Sampling optimization based on secondary information and its utilization in soil carbon mapping, 133, 345–362. https://doi.org/10.1016/j.geoderma.2005.07.020

Sankar, G., Kumar, P., & Chattopadhyay, R. (2018). Annals of Agrarian Science Assessment of spatial variability of soil properties using geostatistical approach of lateritic soil (West Bengal, India). Annals of Agrarian Science, 16(4), 436–443.

Stumpf, F., Schmidt, K., Goebes, P., Behrens, T., Schön Brodt- , S., W d ux, ., … S h l , T. (2017). Catena Uncertainty-guided sampling to improve digital soil maps. Catena, 153, 30–38. https://doi.org/10.1016/j.catena.2017.01.033

Szatmári, G., László, P., Takács, K., Szabó, J., & Koós, S. (2018). Geoderma Optimization of second-phase sampling for multivariate soil mapping purposes: Case study form wine region, Hungary, (February). https://doi.org/10.1016/j.geoderma.2018.02.030

Van Groenigen, J. W., S. A. (1998). Constrained Optimization of Spatial Sampling using Continuous Simulated Annealing. Environ. Qual.

Van Groenigen, J. W. (2000). The influence of variogram parameters on optimal sampling schemes for mapping by kriging. Geoderma, 97(3–4), 223–236. https://doi.org/10.1016/S0016-7061(00)00040-9

Van Groenigen, J. W., Siderius, W., & Stein, A. (1999). Constrained optimisation of soil sampling for minimisation of the kriging variance. Geoderma, 87(3–4), 239–259. https://doi.org/10.1016/S0016-7061(98)00056-1