Efficient soil depth sampling scheme using geostatistics: Case of Maamora forest (Morocco)

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Abstract
Soil is the most important factor precluding cork oak regeneration in the Maamora forest. Regeneration and reforestation success rate depends on upper soil layer thickness, which is sandy and resting above a clay layer. This study was conducted in order to assess sand thickness and to recommend a reasonable and efficient sampling grid that will minimize mapping cost. To achieve this goal, 1912 plots have been collected according to a systematic sampling grid of 500 –m. In addition, and to better understand sand thickness variability, another sampling scheme concerned one stand. It consists of systematic points located at 100 –m distance. The data have been processed using ordinary kriging. The results show that sand thickness is variable and is not related to terrain slope. Also, within a sampling grid of 500 –m, only around 40% of the sand thickness is spatially auto-correlated. Furthermore, there is an anisotropy in the variation of the thickness of the sand. As conclusion, a systematic sampling grid with plots within 200 to 350 m distance seems to be well suited.

Keywords: Geostatistics, Kriging, Anisotropy, Maamora, Sand Thickness, Sampling, Variogram.

Introduction

Forest restoration is constrained by a set of sites factors related to natural condition or to human-induced disturbances. These factors acts in both micro and meso-scales (Kauano et al., 2013) and include many biophysical variables such as the degree of forest fragmentation, the levels of soil fertility, the topography and the microclimates across the landscape (Lamb and Gilmour, 2003). Within a specific ecoregion soil and slope aspect remain the main factors that underpin the success of restoration activities. As result of the environmental factors interaction, soil properties vary spatially (Di et al. 1989) and tend to be correlated both vertically and horizontally (Warrik et al. 1986). Such spatial variability is a key factor for predicting sites ability to undergo forest restoration activities or to study species suitability to that sites (Bagaram et al. 2016).

Maamora is the largest cork oak forest in the world with regard to area, it covers 133,000 ha. Nevertheless, cork oak stands represent only 70,383 ha. Spatially, cork oak cover has experienced a regression trends estimated to 30% during the period between the two latest management plans (Mounir, 2002). To mitigate that regression, forest services launched huge plantations actions. Results of such actions have been very hazardous/capricious. Studies regarding cork oak regeneration, carried out in Maamora, highlighted that water balance (climate and soil factors) in addition to human pressure are the main limiting factors to cork oak regeneration (Marion, 1951; Artigues and Lepoutre, 1967; Lepoutre, 1965; Belghazi et al., 2001, 2011; Cherki et Gmira, 2013; Bagaram, 2014; Lahssini et al., 2015; Bagaram et al., 2016). Further, these studies showed that sandy layer thickness contribute highly to explain plantation success or failure.

Despite the importance of the sand thickness factor, managers face the lack of a sand depth map covering all the forest. Previous study was conducted at small scale through a 40 –m grid (Lepoutre, 1965). Therefore, within the scope of the latest forest management plan (HCEFLCD, 2011), soil samples have been collected according to a regular grid with an interval of 500 –m in order to produce a map of the sand layer thickness. Interpolation was based on the inverse distance method. However, this method is biased, has no statistical foundation and its accuracy cannot be assessed. Indeed, as highlighted by Rossiter (2013), both the power and the limiting radius could not be chosen objectively when using inverse distance interpolation method. Therefore, assessing the sampling scheme and improving the interpolation quality will contribute highly to improve our understanding and the quality of future maps.

Even though spatial interpolation methods are multiple including: i) deterministic methods (barycentrics, cubic adjustment, etc) and ii) stochastic (local regression, classic regression, kriging) (Baillargeon, 2005), their complexity and effectiveness are different (Renard and Combi, 2007). Kriging estimator is unbiased and the method is the only one that considers spatial dependence structure of data. The principle underneath kriging suggests that the correlation between pair points decrease with an increasing lag distance (regionalized variable). The variogram is the model analyzing the structure of spatial dependence. It reflects the degree of similarities between sample data separated by a lag distance (Akhavan et al., 2010).

The sampling scheme to get data plays a crucial role for the prediction quality achieved by kriging. Therefore, Van Groenigen (2000) suggests that sampling scheme should be the starting point of any geostatistical study. Furthermore, as stated by Lark (1999) and Heil and Schmidhalter (2012), soil data are relatively costly. Hence, certain ancillary variables, which are related directly or indirectly to soil properties, can be collected in large numbers at low cost.

In the case of the Maamora forest, the interpolation quality (from punctual data) could be highly improved using an appropriate sampling grid. Also, it is assumed that sand thickness is correlated with terrain slope. For example, as erosion drains soil toward lower slopes, sand thickness might be lower on steep slopes.

This study aims to determine the efficient interval for a systematic sampling grid in order to produce maps of sand thickness and slope of the clay layer of the Maamora forest. Also, as terrain slope is easier to collect, we would like to verify the hypothesis that this variable is related to sand thickness; if such hypothesis is verified, sand layer thickness will be easily estimated.

2. Materials and methods

2.1. Study area

As shown in **figure 1**, the Maamora forest is located nearby Rabat. The forest is formed by five different blocks named from west to east Cantons A, B, C, D, and E. Regarding the classification of Emberger (1955), the bioclimate of the study area is sub-humid in the western part and semi-arid in the central and eastern parts of the forest. The soils consist of a sandy layer covering a clay layer with a transition that can be sharp to smooth (Lepoutre, 1965). The same author described four types of soil: shallow beige sands on clays, deep sands on clay, red sands on clay, and hydromorphic soils with a low lateral drainage.

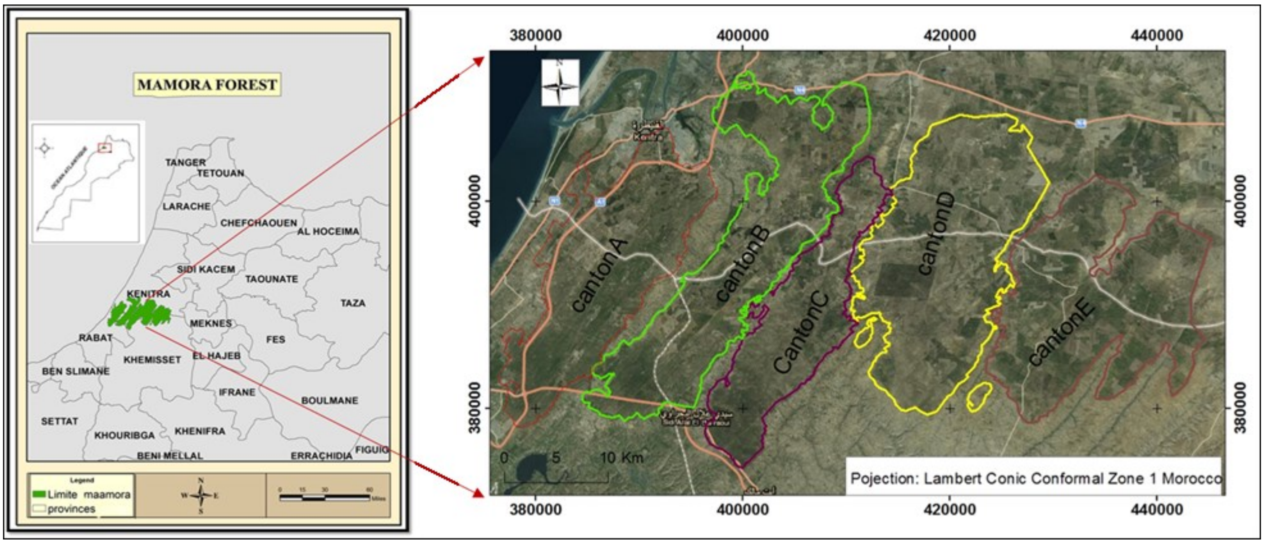

Figure 1. The Maamora forest location and its cantons.

2.1. Sampling strategy

Regarding cork oak regeneration success in the Maamora forest, soil water balance seems crucial. Moreover, the main involved soil factors are sand layer thickness and the clay layer slope. The sampled points were identified according to a regular grid with a sample point each 500 –m (one sample per 25 ha). Each node of the grid, was identified using a GPS receiver (Trimble™ Juno SB with an accuracy of ± 5m). Then, sand layer thickness was measured with a soil auger and terrain slope was measured with a clinometer (in order to look for any other correlation between sand layer thickness and other environmental predictors). A systematic grid was adopted because it is considered to have the best precision (Webster and Oliver 1990).

In addition to the 500 –m regular grid, another regular grid with a 100 –m interval between samples (one sample per hectare) have been established at one stand scale. As shown in **figure 2,** the selected stand for the fine scale sampling (grid of 100 –m) is more or less homogenous compared to that for the coarse scale of 500 –m. A further simulation was done by only considering a rectangular grid of 100 X 200 –m, this by simply leaving out one sample out of two (one sample per 6 ha). Indeed, many authors recommend a sample size of 100 to 150 sites in order to have a stable variogram (Voltz and Webster, 1990; Webster and Oliver, 1992; Kerry and Oliver, 2007) and all the three considered grids fulfill this condition. Nevertheless, a fourth grid has been considered by keeping only one quarter of the data. This means a regular sampling grid of 200 –m (one sample per 4 ha). In fact, some authors used only around 50 sample sites to estimate the variogram (Marchant et al., 2005) or even less (Allen et al., 2010; Hosseinalizadeh et al., 2011; Andrea and Pasquale, 2014).

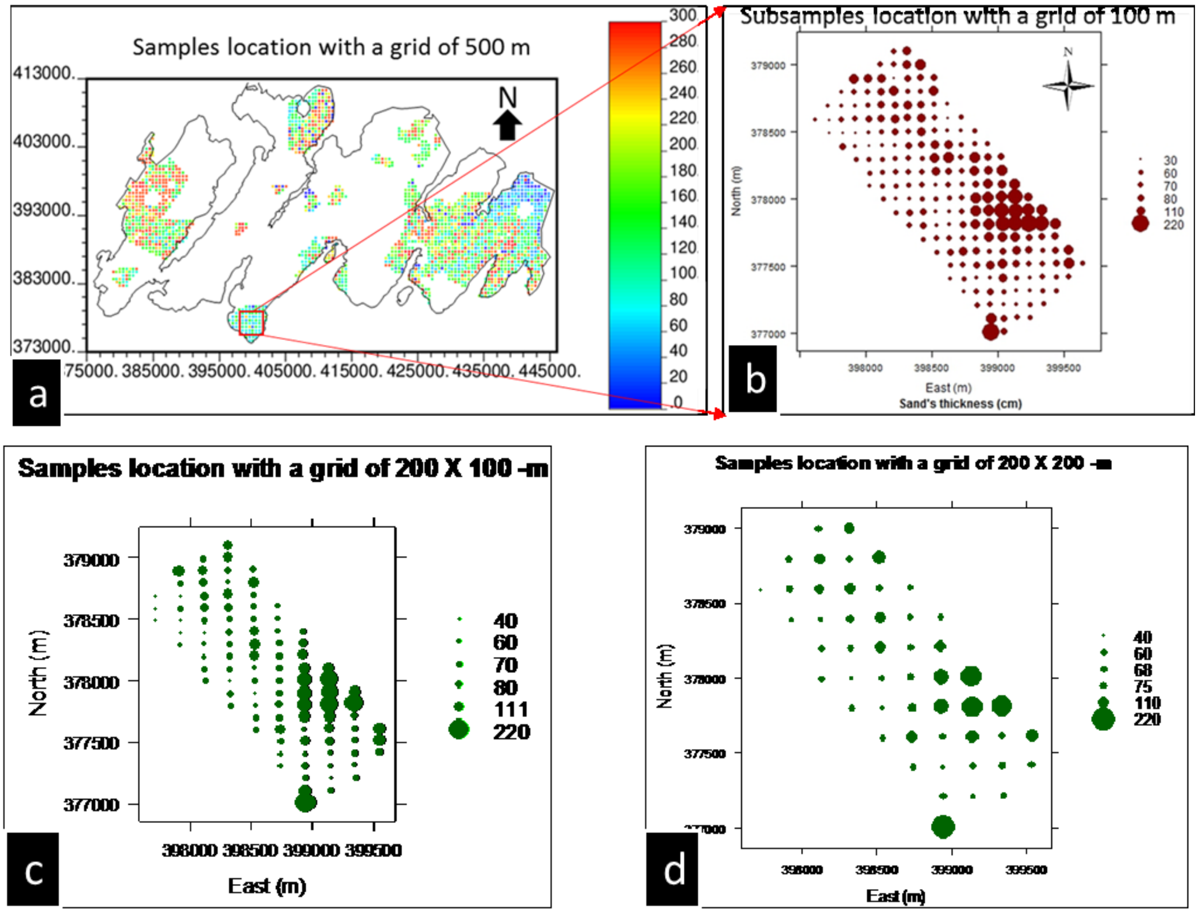

Figure 2. Sample points location in the Maamora forest: a) a regular grid of 500 –m, b) a regular grid of 100 –m, c) a rectangular grid of 200 X 100 –m, and d) a regular grid of 200 -m.

2.2. Spatial interpolation

Using the surrounding samples, spatial interpolation consists of estimating values at places where no sampling was carried out. There are multiple methods for spatial interpolation such as Thiessen polygons, inverse distance, spline, etc. Each of these methods presents some limitations. To overcome these limitations, the geostatistical method of spatial interpolation (kriging) was developed (Matheron,1963). In kriging, the variogram is the corner piece. It analyzes the spatial dependence structure and could be computed according to **equation 1**. The structure of the variogram can differ depending on the direction (anisotropy). As our sampling dataset is relatively large, anisotropy was analyzed in the main directions.

However, depending on data and goals, the form of interpolation may differ. Hence, to overcome the problem facing the choice of the right spatial interpolation method, Hengl (2007) proposed a decision tree. In order to produce a sand layer thickness map, the ordinary kriging (OK) is highly suitable. Variogram modeling allows to fit a theoretical model to experimental data (Webster and Oliver, 2000; Akhavan et al, 2010). The quality of the adjustment was assessed by a long range, a very high partial sill and a low nugget effect indicating the highest structured part (SP) known as spatial dependence (ratio of the partial sill over the total sill) (Akhavan et al, 2010) or low error that is the ratio of the nugget effect over the total sill (Siqueira et al., 2015; Wang et al., 2015).

Variogram was fitted using statistical least squared method implemented within *gstat* library (Pebesma, 2004). This library is freely downloadable from the website http://www.gstat.org. The R project environment (R core team, 2015) was used either for *gstat*, for variogram fitting, graphical purposes or other statistical analyses.

The experimental variogram is computed, through binning data into distance classes, using **equation 1**, with parameters $\gamma_e(h)$ the Experimental semivariance for the lag separation h, *N(h)* the number of pairs with points spaced by the lag h, $z(x_i)$ the observed value at location i, and $z(x_i + h)$ the observed value at a location h farther from i.

$$\gamma_e(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \left[z(x_i) - z(x_i + h) \right]^2 \tag{1}$$

Then, **equation 2** gives estimated value at any point where λ_i is the weight associated with each sample location value. Within a probabilistic framework, kriging attempts to minimize the expected mean square error under the constraint of unbiasedness. Hence, kriging is the Best Linear Unbiased Estimator (BLUE) as:

$$\hat{\ } \qquad \sum_{i=1} \lambda_i z(x_i) \tag{2}$$

$$\sum_{i=1}^{n} \lambda_i = 1 \tag{3}$$

In order to assess the quality and to validate kriging results, Leave-one-out cross validation (LOOCV) was used. It consists, for each point, to leave it out (to not include it in variogram fitting dataset) and then to predict at this point location the value and to proceed with the next data point. Errors are obtained by subtracting, for each point, predicted value from observed one.
The precision of the prediction is given by the mean error (ME) or the root mean squared error (RMSE). The kriging interpolation is good as ME is close as possible to 0 and RMSE the lowest.

$$ME = \frac{1}{N} \sum_{i=1}^{N} \{ z(x_i) - \hat{\ } \tag{4}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left\{ z(x_i) - \hat{\ } \right.} \tag{5}$$

3. Results and discussion

3.1. Exploratory data analysis

Descriptive statistics, including mean, coefficient of variation (CV), minimum and maximum are presented in Table 1. The mean and median values were used as primary estimators of the central tendency. The dispersion was assessed through the variance, CV, minimum, and maximum. Within the scope of 500 –m sampling grid, 1912 sample points (sites) were measured. The sand thickness ranges from 20 to 310 cm with an average of 174 cm and the variability is around 45%. Average terrain slope is 5.54% and ranges from 0 to 43%. There is an important variability in the terrain slope (101%). In addition, for the 100 –m square grid, 201 samples were measured. The sand thickness remains highly variable. The same pattern is observed when using a rectangular sampling grid of 200 X 100 –m and the regular sampling grid of 200 –m (**Table 1**). Indeed, unlike what is widely supposed, sand thickness does not seem to be related to terrain slope as R^2 is only about 0.3‰. For the same terrain slope value, there is a large variety of observed sand thickness values (**Figure 4**).
Soil properties can vary due to intrinsic or extrinsic sources of variability. As descriptive statistics cannot discriminate between these two sources of variability (Wang et al., 2015), spatial autocorrelation structure of sand thickness was further investigated.

Table 1. Descriptive statistics of the collected data in the Maamora forest.

Variable	Grid (m)	Number of samples	Mean	Median	Min	Max	SD	CV
Slope (%)	500	1912	5.54	3	0	43	5.6	101
Sand thickness (cm)	500	1912	173.98	165	20	310	78.8	45
Sand thickness (cm)	200	50	84.7	75	35	220	42.0	48
Sand thickness (cm)	200*100	100	85.94	72.5	40	220	37.1	43
Sand thickness (cm)	100	201	84.31	70	30	220	35.9	42

Min=minimum ; Max=maximum ; CV=coefficient of variation ; SD= Standard Deviation.

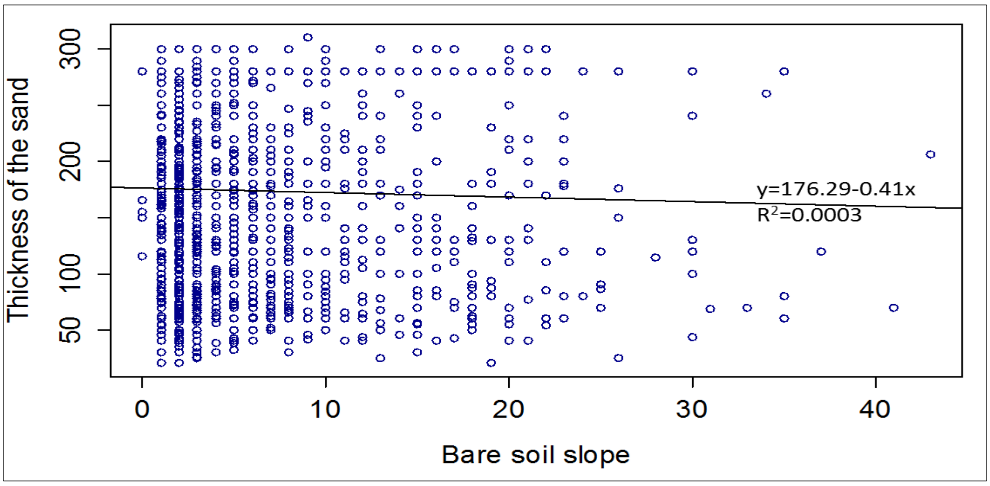

Figure 4. Linear regression between bare soil slope as independent variable and sand thickness as dependent variable.

3.2. Spatial variability of sand thickness

3.2.1. Square grid of 500 –m

Variogram surface shows that spatial dependence is not the same in all directions. There is a greater spatial dependence (maximum continuity) in the north-east direction compared to the perpendicular direction to that one (Figure 5). Furthermore, computing the semivariograms in both directions confirmed the anisotropy. It is a zonal anisotropy as the sills in both directions are not the same (Kerry and Oliver, 2004), even though the geometric anisotropy is the most common (Oliver and Webster, 2014). Both semivariograms have been fitted by a spherical model (Herbst et al., 2012). In the north-east/south-west direction (maximum spatial continuity), the range is 12,769 m with a nugget effect of 3,623 cm^2 and a partial sill of 3,170 cm^2. This gives a structured part (SP) of 46.7% or an error (nugget to sill ratio) of 50.3% (**Table 2**).This means that only 46.7% of the thickness of the sand is spatially autocorrelated. A spatial dependence error exceeding 50% is very high. The direction of the low spatial dependence is characterized by a range of 1,592 m (around three times the sampling grid) and an error of 70.7%. Another fact which needs more attention is that the variability is not the same in both main directions.

The nugget effect is very high. It could be explained by a large interval between samples within a sampling grid (Akhavan et al, 2010) or to the outliers within data (Oliver and Webster, 2014) or to the sampling errors (Burgos et al., 2006; Dubrule, 1993) or to the microstructure in the data or to an undetermined mixture of both microstructure and human errors (Dubrule, 1993). In our case, there are no apparent outliers in data. Then, the high nugget effect could relay in our case on the sampling scheme or microstructure or to human errors in data collection.

During the interpolation using kriging, the surrounding points and their spatial arrangement are the main element taken into account. Shorter distances matter the most in interpolation. Then, having a SP very high with shorter range will be very valuable. Therefore, and in order to understand why we got a high nugget effects, the stand level 100 –m square grid have been used.

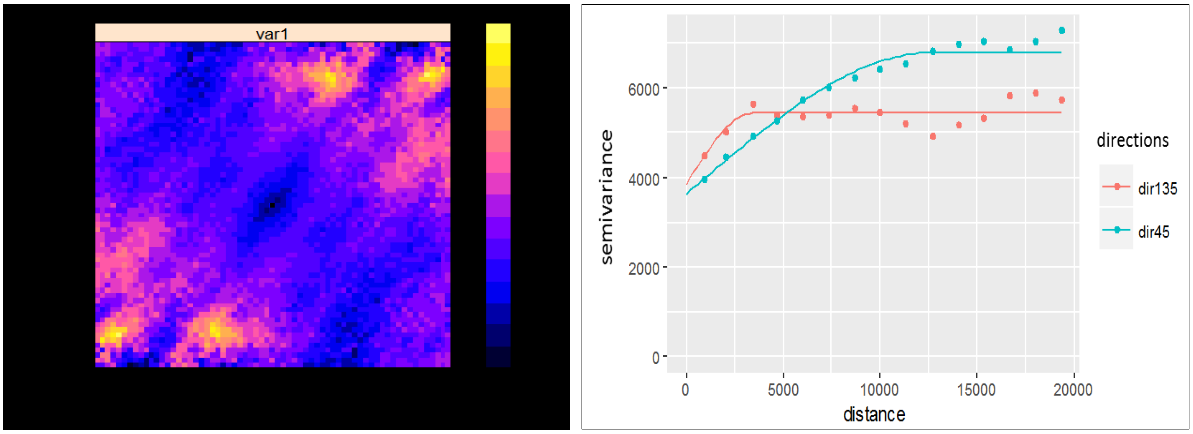

Figure 5. Left: surface variogram of sand thickness; right: experimental variograms fitted by theoretical variograms in the main directions of anisotropy (direction 45°, the green line and direction 135°, the red line) to the 500 –m grid samples.

Table 2. Parameters of the models adjusted to the experimental variograms from the 500 m grid.

Models	Direction	Nugget (cm^2)	Partial sill (cm^2)	Range (m)	SP (%)	Error (%)
Spherical	45°	3623	3170	12769	46.7	53.3
Spherical	135°	3843	1592	3420	29.3	70.7

SP is the ratio of "partial sill" over the "total sill" and error=1-SP.

3.2.2. Square grid of 100 m

The regular sampling grid of 100 –m confirmed the anisotropy detected in the whole forest using a sampling grid of 500 –m. Unfortunately, due to the lack of data (only 201 sampled sites), stable directional viariograms could not be fitted. However, the omnidirectional variogram in **figure 6** provides valuable information. It was fitted with a spherical model with a range of 659 m, a nugget effect of 175 cm² and a partial sill of 1,259 cm². This leads to an SP of 88%. As the error is only of 12%, it could be concluded that sand thickness is strongly spatially auto-correlated (Cambardella et al., 1994; Wang et al., 2015). Furthermore, the high nugget effect in case of 500 –m sampling grid is due to the sampling grid that is too large to observe soil variability (Akhavan et al, 2010).

To sum-up and as highlighted previously, using a 500 –m sampling grid does not allow to take into consideration a great part of sand thickness variability. Hence, in order to produce a more precise sand thickness map for the Maamora forest, the sampling grid should be improved.

3.2.3. Rectangular grid of 200 X 100 m

By keeping only half of the data set (removing 101 sites and keeping 100), a sampling grid of 200 X 100 –m has been used to simulate the effect of larger interval between sample locations. The fitted spherical variogram to the experimental variogram, shown in **Figure 7**, has a range of 666 m, a nugget effect of 160 cm² and a partial sill of 1,304 cm². This corresponds to an error of 10.9% (SP of 89.1%). The structure of the variogram did not really change with this sampling grid. This shows that we do not really lose in precision by using a rectangular sampling grid of 200 X 100 –m instead of the regular sampling grid of 100 –m. Contrarily, we reduce the sampling cost as we reduce the sample size by half. Moreover, this shows that the nugget effect observed with the sampling grid of 100 –m is mainly due to the sampling errors or a microstructure and not to sampling grid scheme.

3.2.3. Square grid of 200 m

With a regular sampling grid of 200 –m, the variogram does not show any nugget effect. The spherical model fitted shows a range of 655 m and a sill of 1,893 cm² and no nugget effect. This corresponds to an SP of 100% (**Figure 7**). Fitting such models with no nugget effect means we assume there is no sampling error or other sources of errors in the measurement (we have a strong confidence in our data) while this is not actually the case (Clark, 2010; Andrea and Pasquale, 2014). Clark (2010) suggested to have a nugget effect because the less we trust our data the more confident we get in the results.

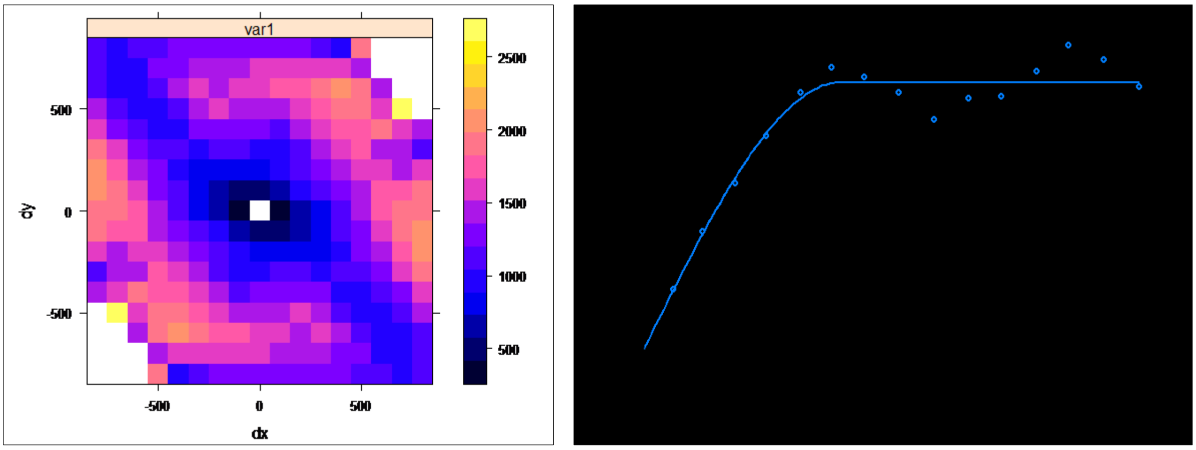

Figure 6. Left: surface variogram of sand thickness; right: experimental omnidirectional variogram fitted by theoretical variogram for the 100 –m grid.

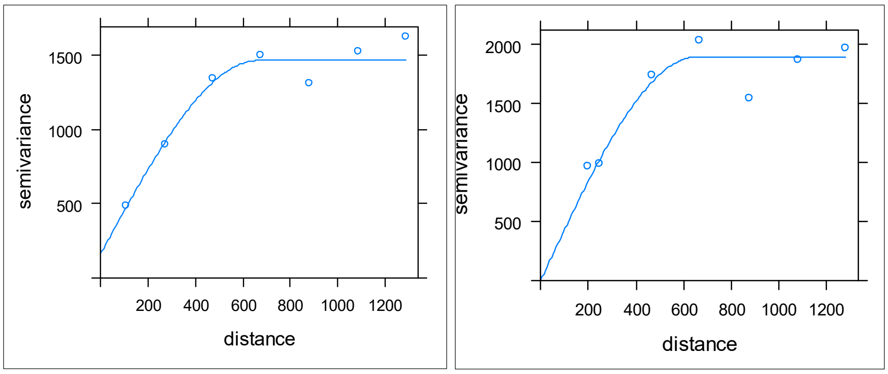

Figure 7. Experimental variogram fitted by a spherical model for a set of samples with a rectangular grid of 200 X 100 –m (right) and regular grid of 200 –m (left).

As the lag size (interval between sample points) increases, we expect the error to increase. However, the results obtained here are a bit strange. It shows that by increasing the sampling interval from 100 –m to 200 –m, the spatial autocorrelation increases. Nevertheless, spatial autocorrelation decreases when the sampling interval is increased up to 500 –m. Akhavan et al. (2010) obtained a similar result where by increasing the number of samples by decreasing the lag size, the spatial dependence decreased.

3.3. Kriging

The results of kriging and cross validation using the four sampling grids show that the predicted and the observed data values are close but the predicted data have a narrower range **(Tables 1** and **3)**. This is typically the kriging characteristic that tend to smooth data. Regarding the errors, all the grids display ME close to zero. However, the ME is not the good indicator to select the best kriging due the fact that positive and negative errors are integrated. The RMSE is higher with the sampling grid of 500 –m, while it is lower with the three other grids. To select the appropriate sampling grid, besides the SP related to the variogram, RMSE should be taken into account. In this study, the regular grid of 200 –m gives better results compared to those obtained with a regular grid of 100 –m.

Table 3. Results of kriging and cross-validation for the 4 grid sizes.

Grid (m)	Mean (cm)	Min (cm)	Max (cm)	SD	CV(%)	ME	RMSE
500	174.0	51.8	268.7	43.9	25	-0.017	65.1
200	84.5	41.9	175.7	28.2	33	0.189	25.2
200*100	84.6	45.3	166.6	26.5	31	0.144	25.5
100	84.3	43.5	185.3	28.4	34	-0.034	22.2

RMSE= Root Mean Square Error; SD=Standard deviation; ME=Mean Error; CV=coefficient of variation.

The SP used to assess variograms presents one flaw. It is possible to force a variogram to have a nugget effect different from the one it should have since the nugget effect is the intersection of the variogram with the y-axis and is not real measurement (Clark, 2010; Andrea and Pasquale, 2014) and since it is used in the calculation of SP, hence SP does not seem to be the appropriate tool to compare to compare variograms. On the other hand, RMSE appears to be a good indicator of a chosen model. The RMSE gives the average error on the values estimated using the fitted variogram model. In this paper, the three grids, namely, regular grid of 100 –m, regular grid of 200 –m, and rectangular grid of 200 X 100 -m give almost the same RMSE.

As concluded by other authors (Guan et al., 2004; Bowman and Crujeiras, 2013), another aspect worth and should be taken into account when designing the sampling scheme is the anisotropy. Furthermore, Kerry and Oliver, (2003) advised using a sampling grid just-lesser than the half of the range may be sufficient, which mean in our case a regular grid of less than 330 –m. This suggested sampling grid even though different from the ones used in this study make sense as the variography sampling scheme can be different from the sampling scheme designed for kriging interpolation (Marchant and Lark, 2012). Our results showed that this sampling grid is too big to map efficiently sand thickness in the Maamora forest.

Conclusion

The sampling scheme is very important to assess the sand thickness in the Maamora forest. There is no relationship observed between the thickness of the sand and the terrain slope. The 500 –m sampling grid is too large to take into consideration sand thickness variability in the Maamora forest. Such variability is not the same in all directions and an important anisotropy have been revealed. The spatial autocorrelation is very low in the direction north-west/south-east with a lower variance. In addition, sampling each 40 –m, as this had been done in an earlier study, is not justified. Then, efficient sampling could be characterized by systematic grid with sampling points regularly distributed at distance ranging from 200 to 350 –m. The sampling grid can be rectangular in order to take in advantage of the anisotropy and to reduce the costs related to data collection. The further analysis would be to enlarge the size of the selected parcel to check these findings. Finally, there is no linear relationship between terrain slope and the thickness of the sand layer. Therefore, the former cannot be used to predict the latter in the Maamora forest.

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Conflicts of Interest: The authors declare no conflict of interest.

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