Industrial Crops and Products 91 (2016) 231–237

Contents lists available at ScienceDirect

Industrial Crops and Products

journal homepage: www.elsevier.com/locate/indcrop

Assessment of spatial uncertainty for delineating optimal soil sampling sites in rubber tree management using sequential indicator simulation

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ARTICLE INFO

Article history:
Received 16 February 2016
Received in revised form 2 July 2016
Accepted 19 July 2016
Available online 26 July 2016

Keywords:
Categorical variables
Rubber trees
Sequential indicator simulation
Soil sampling sites
Spatial uncertainty management

ABSTRACT

Where and how to sample soils in highly variable tree plantations are important to soil testing and nutrient recommendation for rubber trees (*Hevea brasiliensis*). The objectives of the study were to determine optimal sampling sites representing means of key soil nutrients at micro scale and to delineate probability maps for optimal soil sampling sites for nutrient management planning for rubber trees. The study was conducted in a rubber tree plantation in the tropical island of Hainan, China in 2011. A total of 168 soil samples (0–0.2 m in the soil depth) were collected in a 1 m × 0.5 m grid in equivalent rectangles. The air-dried soil samples were then analyzed for total nitrogen (TN) and soil organic matter (SOM) variables. Using the sequential indicator simulation (SIS) we discovered that sampling sites were with high probability for both soil TN and SOM within 10% relative standard deviation above and below the means. The high probability regions of uncertainties were near the rubber rhizome neck areas and in the shrub and ruderal zone in the high locations, where were no-tillage zones and at the specific non-cultivated land between the adjacent rubber planting strips with natural vegetation growth. The spatial variability in TN and SOM variables could be attributed to the combined effects of topographic micro-features and tree management practices. It was concluded that SIS method could be useful for effective determination of optimal sites for soil sampling for spatial uncertainty and nutrient management in rubber tree plantations.

1. Introduction

Rubber tree (*Hevea brasiliensis*) is one of the main economic species for many tropical countries in Asia, South America and Africa (IRSG, 2010). In China, rubber plantation areas have reached 980×10^3 ha in 2009 with approximately 47% of the total planting areas found in Hainan Island, southern China (Mo, 2010). Rubber tree plantations, covering 13.8% of the total land area of Hainan Island, have become the largest artificial ecosystem in the island. Rubber trees are grown for latex extraction, which is done using a multiannual tapping system that can last from 15 to 30 years or even longer when management practices are adequate (Michels et al., 2012). There have been insufficient soil nutrients in rubber plantations due to daily extraction of latex (Cheng et al., 2007). It is absolutely necessary to add sufficient chemical fertilizers in order to sustain rubber tree growth and maintain high yield of latex (He et al., 1992).

While nutrient supplies are very important to enhance rubber productivity of the trees for a long period of production, there has been a serious difficulty on how to meet the nutrient requirements of the trees effectively. At present, the best fertilizer recommendation models are based on both foliar and soil nutrient status of rubber trees (Chen et al., 2011). However, management practices such as fertilizing in specific caves and building contour ledges in rubber plantations often cause a highly spatial variability in surface soil nutrients (Lin et al., 2013). Where and how to obtain representative soil in the highly variable topsoil are important to conduct soil testing and nutrient recommendation. Such problems exist not only in rubber tree plantations but also in other long-term cash tree plantations such as mango orchards and citrus orchards in general.

Abbreviations: K-S, Kolmogorov-Smirnov; MSIS, multiple sequential indicator simulation; RSD, relative standard deviation; SGS, sequential Gaussian simulation; SIS, sequential indicator simulation; SOM, soil organic matter; TN, total nitrogen.

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http://dx.doi.org/10.1016/j.indcrop.2016.07.030
0926-6690/

At present, the conventionality soil sampling site in rubber plantation is in the shrub and ruderal zone, where is at the specific free land between the adjacent rubber planting strips with vegetation growth of controlling nature (He and Huang, 1987). Whether it could reliably represent the nutrient level in the rubber plantation was unknown. Determining soil nutrient variability and then putting forward feasible soil-sampling schemes to obtain a reliable representative sample is the key to successful fertilizer recommendation and environmental monitoring and assessment for rubber plantations.

The kriging estimation has proven to be one of the most efficient geostatistical methods in characterizing and predicting the variability of soil attributes (Ersahin and Brohi, 2006; Sun et al., 2003; Baxter and Oliver, 2005; Lauzon et al., 2005; Chen et al., 2006). However, the smoothing effect of the kriging method results in less variation in the estimated values than in the observed values (Oliver and Webster, 2014; Hofer et al., 2013). Recently, stochastic simulations such as sequential Gaussian simulation (SGS) and sequential indicator simulation (SIS) have been developed and applied to reduce the inherent limitations in kriging analysis (Deutsch and Journel, 1998; Goovaerts, 1997). The simulation approaches take into account both spatial variation of the observed data at sampling sites and variation in the estimations at unsampled sites (Juang et al., 2004). Therefore, data should be treated as a whole to recover the spatial structure aiming to estimate the real spatial distribution, not just to minimize a local error variance (Li et al., 2008). Moreover, information generated by sequential Gaussian simulation (SGS) or sequential indicator simulation (SIS) techniques seems more realistic (Zhao et al., 2005).

The direct use of stochastic simulation to quantify the spatial uncertainty has gradually become a powerful tool in geostatistical studies. For example, the SGS technique was used to map the spatial distribution of soil water content and provide a quantitative measure of its spatial uncertainty in an 18 ha erosion experiment field in Lower Austria (Delbari et al., 2009). The SIS method was applied for quantitatively assessing the uncertainty in mapping soil organic carbon concentrations in Hebei Province, China (Zhao et al., 2005). The SIS was also used to simulate spatial patterns of forest type (Feng et al., 2006).

The SGS method assumes that data should follow multi-gaussian distribution. However, as a method of non-parametric conditional simulation, SIS does not require any assumption for the shape of the conditional distribution (Goovaerts, 2001). Most of the existing studies have been conducted to assess the spatial changes of continuity variables, with few studies for the measurement of categorical variables (Feng et al., 2006). In addition, there are rarely studies of applying conditional simulation to simulate the optimal soil sampling sites in tropical production systems.

The objectives of the current study were to determine the optimal sampling sites representing the means of key soil nutrients at micro scale through assessing the spatial uncertainty in rubber tree plantations and to delineate the probability maps for optimal sampling sites for rubber tree nutrient management planning and environmental monitoring.

2. Materials and methods

2.1. Study site

This study was conducted in 2011 on a rubber tree plantation of 84 m^2 at Yangjiang State Farm (19°18′47.8″N and 109°45′52.0″E) located in Qiongzhong, Hainan Island, southern China. The local climate was of tropical monsoon type with a mean annual precipitation of 2000 mm and a mean annual temperature of 23.5 °C. The soils were classified as Udic Ferralosols that were derived from granites (Gong, 1999). This soil type was considered as Udic Ferralsol in the World Reference Base for Soil Resources (FAO, 1998), or Oxisol in the USA Soil Taxonomy System (Staff, 2003).

The study area was 14 m × 6 m and the site elevation declined (0.5 m) from the east to the west across the area. There were nine rubber trees planted within the experimental plots (Fig. 1). The distance between two rubber trees in the same row was 7 m, and the distance between two adjacent rows was 3 m. Conventional fertilization caves were situated between two rows and vertical distance was 1.5 m to the rhizome neck. The existing fertilizer recommendations consisted of 2.0 kg compound fertilizers per tree annually, applied in three portions in the middle of March, June and September. North-south contour ledges were built within the plot (Fig. 1). In Hainan, the management practices in selecting sites of fertilizer caves and contour ledge, amounts and types of fertilizers for rubber trees were relatively constant. Rubber plantations were usually located in the hilly areas (Dong et al., 2012). The small plots around nine rubber trees selected in the study were representative of rubber tree plantations.

2.2. Soil sampling and analyses

Soil samples were collected before the third fertilization of the year on August 28th, 2011. The plot was divided into 168 grid-points in equivalent rectangles. Each rectangle sampling grid measured 1 m × 0.5 m (Fig. 1). Within each rectangle, one soil sample was collected using a 8-cm-diameter auger. The sampling depth was 0.2 m as proposed in the conventional soil testing method (Chen et al., 2011; Lu, 1983). Subsoils collected at the fertilization caves were used to preserve the outer edge of the contour ledges in the sampling areas.

The soil samples were then air-dried and ground to pass through a 2-mm sieve. The 168 soil samples were analyzed individually for total nitrogen concentrations (TN) and soil organic matter content (SOM) because these two soil variables were among the most important soil quality components for rubber tree plantations. The TN concentrations were analyzed using the Kjeldahl distillation method and SOM was determined using the potassium dichromate-wet combustion procedure (Bao, 2000).

2.3. Methods of estimation of spatial uncertainty

2.3.1. SIS procedure

The SIS method was applied to assess the uncertainty of optimal soil sampling sites in the rubber tree plantation. The soil sites were divided into two categories, i.e. optimal sampling sites and non-optimal sampling sites. Data sets of soil total nitrogen (TN) and soil organic matter (SOM) were used in the estimation of the spatial soil uncertainty. The SIS procedure can be found in De Cesare and Posa (1995), Deutsch and Journel (1998), Goovaerts (2001) and Webster and Oliver (2007). In summary, the SIS procedure is described as follows:

(1) Suppose that we have observed n sample values $\{Z(x_a), a = 1, 2, \ldots n\}$ for the regionalized variable $Z(x)$. Those sites, whose observed values are within the range of mean ±10% relative standard deviation (noted as category Z), are considered as the optimal soil sampling sites. Then, the observed values $Z(x_a)$ are transformed into indicator codes. If the observed values belong to category Z, we transform them as 1, otherwise as 0. The transformation formula is:

$$i(x_a, Z) = \begin{cases} 1, & Z(x_a) \in Z \\ 0, & Z(x_a) \notin Z \end{cases} \qquad (1)$$