DIGITAL METHODS FOR SOIL MAPPING AND FERTILIZER MANAGEMENT IN OIL PALM

by

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This work is dedicated to my parents.

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KEY TERMS AND ACRONYMS

ASTER — Advanced Spaceborne Thermal Emission and Reflection Radiometer, a 30m global digital elevation model released in 2019.

DEM — Digital Elevation Model, a grid of elevation values.

Fedepalma — A Colombian government agency responsible for the development of the palm oil industry in Colombia.

FFB — Fresh Fruit Bunch, the harvested portion of an oil palm tree.

GAMS — Generalized Algebraic Modeling System, a programming language often used for optimization modeling.

GIS — Geographic Information System, a system designed to capture, store, manipulate, analyze, manage, and present spatial or geographic data.

IGAC — Instituto Geoespacial Agustin Codazzi, the primary geographic institute in Colombia.

ISO-clustering — Iterative Self-Organizing clustering, an unsupervised classification method used to generate optimal clusters between multiple input bands.

MCA — Modified Catchment Area, an iterative terrain algorithm that examines waterflows across a topographic gradient.

MPOB — Malaysian Palm Oil Board, a government agency responsible for the development of the palm oil industry in Malaysia.

NH — Normalized Height, a terrain algorithm that shows relative terrain elevation after normalizing to the mean elevation of the target site.

NPV — Net Present Value, the current value of a cashflow are discounting for the time value of money.

PORIM — Palm Oil Institute of Malaysia, the previous name of the Malaysian Palm Oil Board.

Raster Layer — A pixel based informatation layer in a geographic information system.

SAGA — System for Automated Geoscientific Analysis, a GIS computer program used to edit spatial data.

SRTM	Shuttle Radar Topography Mission, a mission to create a 30m global digital elevation model released in 2015.
TA	Terrain Algorithm, an automated process that analyses a digital elevation model for a specific topographic attribute.
TWI	Topographic Wetness Index, a terrain algorithm that quantifies waterflows from slope and upland contributing area.
Vector Layer	A polygon-based information layer in a geographic information system.

ABSTRACT

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Oil palm (*Elaeis guineensis* Jacq.) is the world's leading source of vegetable oil and an important driver of rural economic activity in Southeast Asia, West Africa, and the equatorial region of Latin America. In the Llanos region of Colombia, palm oil production is additionally an important vehicle for legal employment and social stability in a region deeply affected by the country's longstanding and recently-concluded armed conflict. The economic viability of palm oil production is thus of great interest to both those directly employed in the industry and to the larger society around them, and yet oil palm remains a relatively understudied cropping system.

Spending on fertilizer is one of the largest costs in palm oil production, and plantations face considerable pressure to apply fertilizer as efficiently as possible in order to maintain the profitability of their operations. However, developing strategies for optimizing fertilizer applications in oil palm can be considerably challenging given the particular characteristics of palm oil production systems. Oil palm has a typical life-cycle of 25 years, with harvesting done manually approximately every fifteen days for the duration of the palms productive life-cycle. The morphology of oil palm's reproductive system makes it possible for environmental changes to affect yield in irregular ways, with the same soil or climate-related stressors having the potential to affect yields either immediately or multiple years after the event. It can therefore be difficult for plantations to link changes in yield patterns to individual management changes or environmental factors. Additionally, since unlike all other major oilseeds oil palms must be harvested manually, plantation managers do not have access to the kind of detailed yield data

made possible by mechanized harvesting equipment, but must rely on much more irregular and coarser-resolution information to examine yield variability within plantations. Understanding how the particular soil conditions and fertilizer management history of an individual oil palm plantation drive variability in yields requires employing innovative approaches to maximize the insights to be learned from the available data.

For this study, we worked with a 5,220 hectare oil palm plantation in the Colombian Llanos, in the municipality of Villanueva, Casanare. Despite uniform fertilizer applications and management practices, along with uniform climatic conditions within the plantation, significant yield variability existed within the plantation, with plantation managers initially unable to determine the underlying causes. We proposed and evaluated a methodology for using digital terrain and soil mapping for generating continuous soil data within an oil palm production system, based on Functional Soil Mapping (FSM) methods using the SRTM Global Digital Elevation model and geo-referenced soil sampling, with the goal of identifying soil physical, chemical and hydrological properties that could be directly linked to different yield responses to fertilizer application at the field scale. Furthermore, the economic implications for the plantation of infield variability in yield response to fertilizer arising from variation in soil properties were examined.

The perennial nature and particularities in reproductive morphology of oil palm, including an approximately 8-10 year growth period before mature yields are reached, mean that developing site-specific yield response curves to different nutrient application levels in oil palm requires extensive time and resources. The PORIM model, developed by the Malaysian Palm Oil Board (MPOB) across multiple decades of extensive and continuous field testing, is one of the most commonly used methods by which plantations can estimate yield response at different levels of fertilizer application. Traditionally, the PORIM model is run by using site-specific low-resolution vector-layer soil analysis to adjust various parameters in multiple equation systems developed using statistical methods and many decades worth of field tests by the MPOB. In this study, the PORIM model is used as the basis for a methodology to employ a precision approach to fertilizer management in oil palm using high-resolution raster-layer soil property maps and a constrained-optimization model programmed in the General Algebraic Modeling System (GAMS).

CHAPTER 1. DIGITAL SOIL MAPPING OF AN OIL PALM PRODUCTION SYSTEM IN THE COLOMBIAN LLANOS

1.1 Abstract

Oil palm (*Elaeis guineensis* Jacq.) plantations in the Colombian Llanos face strong pressure to improve fertilizer-use efficiency. Digital soil mapping methods based on topographic analysis using Digital Elevation Models (DEM's) provide an efficient means of quantifying topography-driven variability of soil properties within oil palm plantations. The Shutter Radar Topography Mission (SRTM) Global Digital Elevation Model (GDEM) was used as the basis for modeling topography across an individual oil palm plantation in the municipality of Villanueva, Casanare. Terrain algorithms were used to model terrain attributes and generate continuous soil property maps along topographic soil classes in conjunction with georeferenced soil samples as model inputs. The resulting raster layers of soil property values were evaluated for mean error and their correlation to yield variability across the plantation. Modified Catchment Area (MCA), an iterative measure of a landscape position represented by a grid cell's propensity to lose or gain soil water, was found to have a strong effect on yield, suggesting that soil moisture distribution was an important driver of yield variability in this system.

1.2 Introduction

Advances in the soil and terrain mapping provide new alternatives for capturing within-field variation in Llanos oil palm systems and offer the potential to improve plantation fertilizer management. Within-field soil variation can be a major driver of yield variability in agricultural systems, and modeling soil property distribution in a cropping system can play a key role in improving input use efficiency (Schmidhalter et al., 2006; Xiang et al., 2018). When other factors such as management and input levels are held constant, differences in soil physical, chemical and hydrological properties can result in significant variability in crop yields at the field scale. Changes in soil properties can affect yield by determining the suitability of a soil for the establishment and function of a crop's root system, including affecting the availability and uptake of fertilizer applications (Khan et al., 2005).

Considerable progress has been made in utilizing new technologies in the fields of remote sensing and Geographic Information Systems (GIS) analysis together with traditional methods of soil analysis to generate continuous digital maps of soil properties capable of differentiating field-scale level variability (Odeh et al., 1991). In particular, the ability to generate high-resolution Digital Elevation Models (DEMs) via active remote sensing from spatial platforms has allowed for terrain mapping previously not possible at the scale needed to distinguish in-field variability, and in turn this has made it possible to incorporate topography in mapping the spatial distribution of soil properties (Odeh et al., 1991). Widespread adoption of autonomous geo-spatial positioning technology has also enabled the geo-referencing data points such as physical and chemical soil analysis taken within individual fields, enabling soil mapping methods that use different models of the spatial distribution of soil properties to interpolate between georeferenced samples (Werner, 2001). Together with the increasing availability of yield monitors for many crops, these high-resolution methods of digital soil mapping have enabled new insights into how soil variability relates to in-field yield variability in different cropping systems, including variability in soil moisture and drainage patterns (Iqbal et al., 2005; Xian et al., 2018).

Terrain attributes are DEM-derived environmental variables, which are assumed to integrate surface-controlled processes that relate to the development of different soil properties (Odeh et al., 1991; Florinski, 2016). Terrain Algorithms (TA's) can be used to quantify terrain attributes and analyze the topographic and hydrologic properties of a target location based on a DEM (Florinski, 2016). They have a broad range of uses and applications, including an important role in digital soil mapping. Because the use of TA's to evaluate a location's topography does not rely on on-the-ground surveying, it can offer a cost-effective means of evaluating a target site's topography, particularly in remote areas. Four specific terrain attributes which have been found to be very useful in topographic classification in the Colombian Llanos are: Slope, Normalized Height (NH), Topographic Wetness Index (TWI), and Modified Catchment Area (MCA) from the System for Automated Geoscientific Analyses (SAGA) (Ashtekar and Owens, 2013). Slope is expressed as a percentage, ratio or angle, and describes the proportion of horizontal distance and vertical distance between points, while NH presents the relative terrain elevation after normalizing according to the elevation range within the target site (Boehner and Selige, 2006). MCA and TWI are commonly used to quantitatively describe the effect of topography on hydrological processes and rely on iterative analysis of a digital elevation model to quantify the relative propensity that an individual grid cell will either loose or accumulate water. Modified Catchment Area is calculated via iteration, where the modified catchment area of each grid cell is calculated as a function of slope in angle β and the neighboring maximum values MCA_{max} until results no longer change between iterations.

$$MCA = MCA_{max}(1/15)^{\beta\exp(15\beta)} \text{ for } MCA < MCA_{max}(1/15)^{\beta\exp(15\beta)}$$

Topographic Wetness Index is calculated as,

$$TWI = \ln(\alpha/\tan\beta),$$

where α is the local upslope contributing area and $\tan\beta$ is the local slope.

Both MCA and TWI are capable are estimating both water excess and water scarcity (Jenson and Domingue, 1988; Quinn et al., 1995). These terrain attributes can be used to represent the effect of relief on soil forming factors via water-driven processes (Jenson and Domingue, 1988; Woodrow et al., 2016).

Efforts have been made to use high-resolution soil maps as the basis for variable rate input applications, particularly fertilizer, so as to achieve target yield levels with reduced input use and minimized waste (Schmidhalter et al., 2006; Ashtekar and Owens, 2013; Xiang et al., 2018). Increased spatial precision in decision-making regarding input use can provide benefits to the farm operator by reducing input costs and helping address current impediments to higher production levels, as well as providing environmental benefits by reducing nutrient loss associated with excessive fertilizer applications (Khan et al., 2005). However, different methods for mapping soil properties are often best suited for particular terrains, soil types and cropping systems (Ashtekar and Owens, 2013; Xiang et al., 2018), and developing a method specifically suitable for Llanos oil palm is necessary to determine the potential benefits of new methods and technologies within this specific production system.

The following method was proposed to model terrain as well soil physical and chemical properties within an oil palm plantation and to examine the relationship between variability in these properties and variability in yield. Central to the proposed methodology was the use of publicly available remote sensing data together with georeferenced soil sampling. Specifically, portions of available Global Digital Elevation Models at the 30x30m resolution scale were used as the basis for topographic analysis, and in turn for sampling and modeling soil property distributions across the plantation. The availability of publicly available high-resolution topographic data has made it possible to perform topographic analysis of the plantation with limited resources, more efficiently allocate limited resources for soil sampling and generate continuous soil property maps, using models that relate topographic variability to soil property distributions (Ashtekar and Owens, 2013; Ashtekar et al., 2014). Both soil physical and chemical properties, along with terrain properties pertaining to soil hydrology, are included in the study and continuous soil property distribution maps at the 30x30m resolution were made for each individual soil property. The methods used in this paper for generating continual digital soil property maps are based on the "Functional Soil Mapping" method (Ashtekar and Owens, 2013; Ashtekar et al., 2014), whereby topography is assumed to be the dominant source of soil variability within a target area. This method integrates the SRTM DEM and individual soil property values from georeferenced soil analysis to create continuous soil property maps with a 30x30m resolution for the study site.

The goal of this research was to propose and evaluate a methodology for using digital terrain and soil mapping for generating continuous soil data within an oil palm production system in the Colombian Llanos. Two overarching criteria were set to evaluate the suitability of the proposed methodology: 1) that it be able to capture an aspect of soil variability directly linked to variability in oil palm production at the field scale, and 2) that it could fit within the practical constraints faced by plantation management, including budgetary constraints for equipment or soil sampling, and which was replicable across large areas with minimal labor.

This paper will describe a proposed approach to mapping soil properties in an oil palm plantation in the Llanos, evaluate the accuracy of the resulting predictions for individual soil property distributions, and test whether these distributions appear relevant to yield variability across the plantation.

1.3 Methods

1.3.1 Plantation Practices

The study site was a 5,220 hectare oil palm plantation in the Colombian Llanos, in the municipality of Villanueva, Casanare. The soils of the plantation were uniformly classified as Typic Fluvaquents, with slopes of 0-3%, from recent alluvial deposits from the Eastern Andes mountain range, with a depth greater than 100 cm (IGAC, 2014). Yearly precipitation in the plantation regularly exceeded 2000 mm, while average temperatures were about 27 °C (Table 1.1).

Table 1.1 Yearly precipitation and average temperature in 2010-2016 for a 5,220 ha oil palm plantation in the municipality of Villanueva, Casanare, in the Colombian Llanos.

Year	Precipitation (mm)	Temperature (ºC)
2010	2866	27.0
2011	2195	26.7
2012	2535	26.8
2013	2265	27.0
2014	2116	26.6
2015	1957	27.0
2016	2003	27.2

Following standard practice, palms were planted in triangular patterns with 9 m between palms, with parallel rows established between palm transects and alternatively designated as harvest paths and undisturbed rows[1] (Corley and Tinker, 2008). Each hectare contained 160 palms. The plantation was comprised of six management zones of different size and planted at different times (Table 1.2). Management zones are defined by having been planted at the same time and from the same genetic material, with their exact size and shape determined without definite criteria as the plantation expanded and new plantings were added starting in the 1970's. Since management zones are too large for a harvesting crew to harvest in a workday, they are divided into smaller harvesting units typically ranging between 10 to 20 hectares. There was no consistent methodology used by different plantation's managers to divide management zones into harvesting units as new management zones were added over time, thus they are highly irregular in shape. Yield data for each harvesting unit was collected from 2013-2016.

[1] Undisturbed rows are left unused by machinery and harvest crews

Table 1.2 Management zone size, number of harvesting units (distinct yield points) and year of planting for a 5,220 ha oil palm plantation in the municipality of Villanueva, Casanare, in the Colombian Llanos. Management zones are defined by having been planted at the same time and from the same genetic material.

Management Zone (MZ)	Hectares per MZ	Harvesting Units per MZ	Year of Planting
1	306	12	2004
2	134	9	2004
3	205	10	2004
4	481	23	1999
5	267	10	2005
6	410	14	1990

Management practices and input applications were identical throughout the plantation and followed best practices as defined by the Colombian National Federation of Palm Oil Growers (Fedepalma, 2016). Palms received uniform applications of premixed 13-5-27-5 (N-P-K-Mg as % of total fertilizer weight) fertilizer at the rate of 4 kg/palm from the onset of production, for a total yearly per hectare application of 83 kg/ha N, 32 kg/ha P, 173 kg/ha K, and 32 kg/ha Mg. The fertilizer was a physical mixture of urea, monoammonium-phosphate, muriate of potash, and magnesium oxide.

1.3.2 Digital Elevation Models and Terrain Attributes

The open-source QGIS platform was used for all geographic and terrain analyses. The corresponding sections of both the SRTM and ASTER GDEM's were downloaded from USGS EarthExplorer, and they were clipped to the perimeter of the plantation. Both DEM’s were reprojected to Magna Sirgas Colombia Bogota projection (EPSG 3116), which is based on the national geodetic reference frame used by Colombia's National Geographic Institute Agustin Codazzi. All georeferenced data was thereafter stored and processed in the Magna Sirgas Colombia Bogota projection. Since exact coordinate points for the entire perimeter were not available, the visible outline of the palms from Landsat 8 images was used to create a shapefile of the plantation's outline. A shapefile of the internal boundaries of the plantation's management zones was generated using waypoints from a handheld GPS device.

The SRTM DEM was compared against the ASTER DEM to evaluate for discrepancies using the raster calculator function of QGIS. Terrain analyses were performed using the System for Automated Geoscientific Analyses (SAGA) module. To have a point of comparison between computed MCA values and an infield measurement of soil water, the depth to water table was recorded at the grid cell with both the lowest and highest MCA value within each management zone. Depth of the water table from the soil surface was simultaneously determined one hour after five individual rain events over the course of the 2017 rainy season, specifically the months of May and June, at each selected grid cell by using a 10 cm diameter auger to bore a hole to the water table. Normalized Height, Topographic Wetness Index (TWI) and Slope TA's were also generated from the SAGA module as inputs for the FSM model (Ashtekar and Owens, 2013; Ashtekar et al., 2014) using the 30x30m SRTM DEM.

1.3.3 Selecting Sampling Points for Soil Property Analysis

The selection of sampling points and creation of continuous soil property maps followed the FSM method (Ashtekar and Owens, 2013; Ashtekar et al., 2014). The Iterative Self-Organizing (ISO)-clustering algorithm for unsupervised classification was used to create a soil classification map of twelve distinct classes, using terrain Slope, Normalized Height and TWI as inputs. This algorithm calculated minimum Euclidean distance between each cell in the multidimensional space of the input bands (Pal, 1993). Following classification, probability density functions were determined for each terrain algorithm within each class, with Maximum Likelihood Estimation to determine the distribution parameters (Ashtekar and Owens, 2013; Ashtekar et al., 2014). To create class membership values that followed topographic gradients without artificial hard boundaries, soil similarity vectors were generated to allow each pixel to have partial membership in several classes. Soil similarity vectors contained a partial membership value for each class, such that the sum of all partial memberships in the vector was equal to one.

1)

$$SSV_{xy} = (1, 0, 0, 0, 0, 0, 0, 0, 0, 0)$$

Soil Similarity Vector with full membership in Class 1

$$SSV_{xy} = (.1, .1, .1, .1, .1, .1, .1, .1, .1, .1)$$

Soil Similarity Vector with equal membership in 10 classes

Assignment of partial membership values for each grid cell to each class was done by comparing each grid cell's terrain algorithm values to the previously generated probability density functions according to the FSM method (Ashtekar and Owens, 2013 ; Ashtekar et al., 2014). Grid cells with terrain algorithm values that fit more closely with the probability density functions for a specific class were assigned a higher partial membership value for that class. This method is fundamentally a fuzzy logic-based method, in that a grid cell does not belong to only one class but instead belongs in varying degrees to all possible classes (McBratney et al., 2003;

Ashtekar et al., 2014). Each individual grid cell within the dimensions of the DEM thus comes to possess a vector of soil topographic class membership values, one corresponding to each class. This raster layer of SSV's is used to represent the distribution of membership values in topographic soil classes defined by the terrain attributes of the DEM (Ashtekar et al., 2014).

Sampling locations for soil analyses were selected to maximize the representativeness of each sample for a specific class, i.e. grid cells with the highest membership in one specific class, as described in (Ashtekar et al., 2014). For each of the twelve classes, the four grid cells with the highest membership values for a respective class were sampled (Figure 1.1). Forty-eight locations were thus sampled at three depths: 0-20, 20-40, and 40-60 cm. Samples were collected using a 10 cm Dutch auger to bore to the prescribed depth, and carefully placed in paper bags and labeled for transfer to the laboratory. Soil samples were taken from the undisturbed rows, with one bore taken at the central point equidistant to the three nearest palms (5.2 m from each palm) and three additional bores taken halfway between the centroid and each palm (2.6 m from each palm) (Nelson et al., 2015).

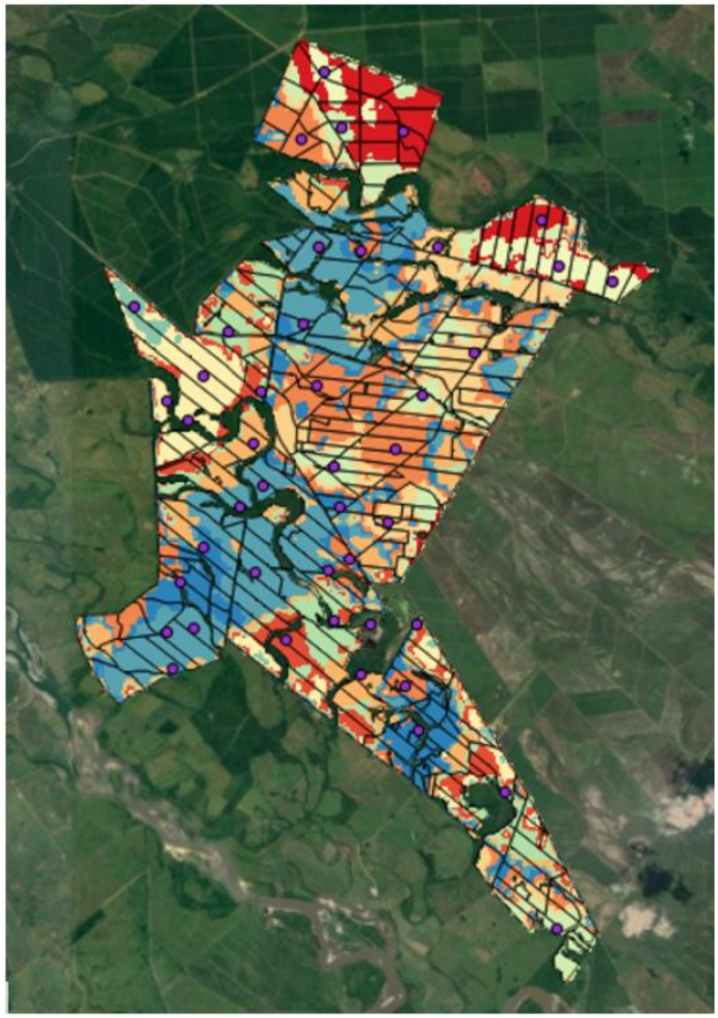

Figure 1.1 Sample locations for a 5,220 ha oil palm plantation in the municipality of Villanueva, Casanare, in the Colombian Llanos. Sample locations were selected from grid cells most representative of a topographic class, defined using unsupervised ISO-clustering of terrain slope, normalized height and topographic wetness index. Each color indicates a different topographic class.

Soil analyses were performed using the standard procedures listed:

-pH: Glass electrode in 1:1 suspension of soil and deionized water (Peck, 1983)

-Texture: hydrometer (Gee and Bauder, 1979)

-Organic carbon: loss-on-ignition, (Golden, 1987)

-Extractable P: Bray II, (Bray and Kurtz, 1945)

-K, Ca, Mg, and Na: ammonium acetate, (Jackson, 1958)

-Exchangeable Al: KCl, (Abreu et al., 2003)

-B, Cu, Fe, Mn, Zn: Mehlich III, (Mehlich, 1984)

-S: monocalcium phosphate, (Peck, 1977)

-ECEC: calculated as the sum of measured cations, (Robertson et al., 1999)

After obtaining the laboratory results for each depth at each sampling location, raster maps of specific soil properties were created using the sample analysis values and the previously generated raster layer of class Soil Similarity Vectors, according to the following equation:

$$v_{ij} = \frac{\sum_{k=1}^{n} S_{ij}^{k} v^{k}}{\sum_{k=1}^{n} S_{ij}^{k}} \qquad 2)$$

Where v_{ij} is the property value at location (i,j), v^k is the representative soil property for soil class k, and n is the total number of soil classes (Zhu, 1997; Ashtekar et al., 2014). One continuous property map was created for each soil property at each depth and stored as separate ASCII files.

1.3.4 Statistical Analysis of Soil Property Raster Data

ASCII files of individual soil properties were uploaded into R as data rasters (Fox, 2005). For each depth sampled, matrix X of georeferenced soil property values was created from the individual soil property rasters. Every element X_{nk} was indexed to a 30x30m pixel n as defined in the SRTM DEM and an individual soil property k.

3)

$$\boldsymbol{X} = \begin{bmatrix} X_{11} & \cdots & X_{1k} \\ \vdots & \ddots & \vdots \\ X_{n1} & \cdots & X_{nk} \end{bmatrix}$$

Where **X** is an (n x k) matrix of soil data,

with n grid cells and k soil properties.

$\bar{X}_k$ was calculated as the mean value for each property k, and the value at 0-20 cm compared with the values at 20-40 and 40-60 cm.

Since oil palm is harvested manually, yield is collected at the level of the harvesting unit. Two hundred and seventy-seven harvesting units existed in the plantation, ranging from 10 to 65 hectares in size. Only a single yield value is reported per harvest for each unit, so any yield variability within each harvesting unit is not observed. Yield information for the plantation was digitized as vector layers of two hundred and seventy-seven yield points, one for each harvesting unit, and indexed by year. These vector layers were rasterized using the GDAL module of QGIS, which creates raster bands consistent with the target vector geometries, and co-registered to match the projection and 30x30meter cell grid of the DEM and soil property rasters. In this way, the vector data from these irregular polygons was reconciled with the raster soil property data for subsequent statistical analysis.

1.3.5 Correlation and Regression Analysis of Soil Property Raster Data

When evaluating the effect of soil properties on yield, the dimensionality of the X matrix was reduced by averaging soil property values, originally at the 30x30 meter resolution, to match the lower resolution of the yield data, resulting in the following reduced matrices:

4)

$$Y = \begin{bmatrix} Y_1 \\ \vdots \\ Y_m \end{bmatrix} \qquad \mathrm{X} = \begin{bmatrix} 1\, X_{11} & \cdots & X_{1k} \\ 1 \quad \vdots & \ddots & \vdots \\ 1\, X_{m1} & \ldots & X_{mk} \end{bmatrix}$$

Where: Y = is an (m x 1) vector of yield values,

m = the number of harvesting units in a management zone

X = is an (m x (k+1)) matrix of soil property data points,

and k = the number of soil variables measured.

The proximity of model prediction values to observed values from the soil samples was assessed with Mean Percent Error (MPE) for each property. MPE was determined by systematically excluding each georeferenced sample point from the model, determining the percent difference between the new estimated property value and the excluded soil analysis value, and averaging the percent difference for each sample point.

5)

$$\mathrm{MPE} = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{y_i - \hat{y}_i}{y_i} \right)^2 \times 100$$

where y_i is the observed soil property at sample location i, $\hat{y}_i$ is the predicted soil property value when y_i is excluded from the model, and n is the number of sample locations.

The correlation of each soil property and yield was determined within each Management Zone using Pearson's Correlation Coefficient:

6)

$$\boldsymbol{r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})}}}$$

where (xi, yi) are paired rank observations, $\bar{x}$ and $\bar{y}$ are the means of the observations, and n is the total number of paired observations.

1.4 Results

1.4.1 Comparison of SRTM DEM and ASTER DEM

When the SRTM DEM was compared to the ASTER DEM, the mean percent difference between co-registered grid cells was 2.0%, with a maximum difference for an individual pixel of 16.8% (Figure 1.2). Areas of maximum distortion between DEM's were scattered around the plantation with no obvious pattern to their occurrence. The SRTM DEM was constructed using interferometric synthetic aperture radar while the ASTER DEM used stereoscopic VNIR images to calculate elevation values. Radar and VNIR light can interact differently with both the atmosphere and the ground surface, potentially arising in small differences in elevation values. The infrequent and minor discrepancies between ASTER and SRTM DEM at our study site are comparable with those observed in previous comparisons of the two DEMs (Arabelos, 2000; Nikolakopoulus et al., 2006). We chose the SRTM DEM for this study to be consistent with previous studies in the Llanos region (Owens et al., 2013) and used it as the basis for terrain analysis, generation of soil property maps and defining the grid structure of all subsequent raster data generated in this study.

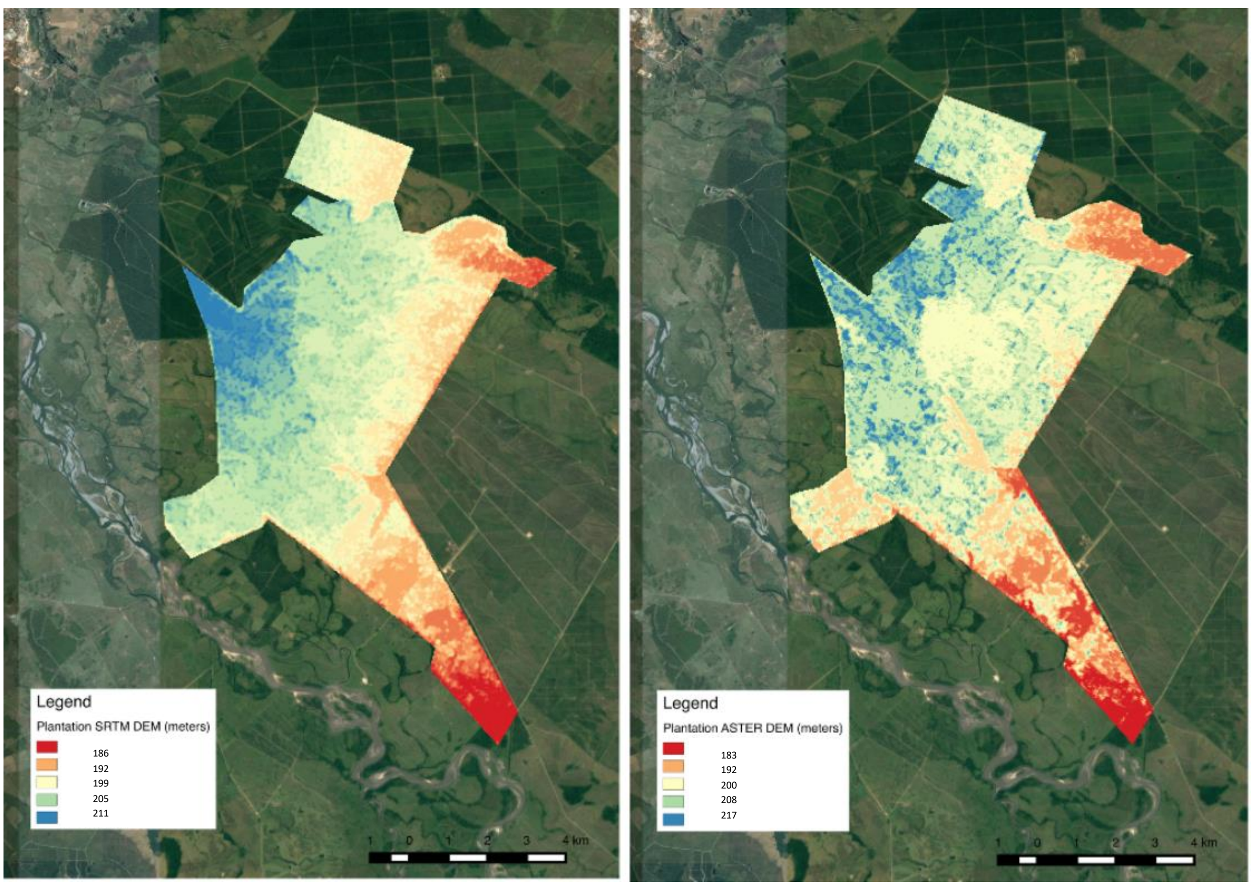

Figure 1.2 SRTM and ASTER 30m Digital Elevation Models for the study site, a 5,220ha oil palm plantation in the municipality of Villanueva, Casanare, in the Colombian Llanos. The mean value for the SRTM and ASTER DEM's respectively was 200±5.8m and 202±7.9m, with an overall difference between both DEM's of 2%.

1.5 Spatial Distribution of Soil Properties and Yield Values

The spatial distribution of soil property values at each depth sampled across the plantation as determined by FSM method (Ashtekar and Owens, 2013; Ashtekar et al, 2014), varied widely by soil property (Table 1.3). Soil exchangeable P showed extreme variation, with a mean of 52 mg/kg and standard deviation of 36 mg/kg at the 0-20cm sampling depth and a mean of 12 mg/kg with a standard deviation of 7 mg/kg at the 40-60 cm sampling depth. Soil pH was the most stable property, with a mean of 5.0 at a standard deviation of 0.2 at the 0-20 cm depth and a mean of 5.1 and 0.2 standard deviation at the 40-60 cm sampling depth. Mean Al and S concentrations increased with depth, while organic carbon, P, K, Mg Fe, Mn and Zn concentrations all declined. Soil texture, pH, Na, Cu and B concentrations were constant across sampling depths (Table 1.3).

Table 1.3 Mean value and standard deviation of soil property distributions across the plantation at 0-20, 20-40 and 40-60cm sampling depths from 144 samples determined by the Functional Soil Mapping method. Forty-eight locations were sampled at 0-20, 20-40, and 40-60cm, with five cores taken per sample. Mean Percent Error (MPE) reflects the accuracy of the model predictions for each soil property. Soil samples were taken from the undisturbed rows between palms, with one core taken at the central point equidistant to the three nearest palms (5.2m from each palm) and three additional cores taken halfway between the centroid and each palm (2.6m from each palm).

	0-20cm	20-40cm	40-60cm	MPE
Sand %	42 ± 5	43 ± 4	43 ± 5	9.2%
Silt %	27 ± 2	25 ± 2	23 ± 2	6.3%
Clay %	31 ± 5	33 ± 4	34 ± 5	12.5%
pH	5.0 ± 0.2	5.0 ± 0.1	5.1 ± 0.2	3.2%
OC %	1.22 ± 0.58	0.58 ± 0.25	0.41 ± 0.19	32.4%
ECEC	5.65 ± 1.84	5.07 ± 1.31	5.11 ± 1.64	21.8%
P (mg/kg)	52 ± 35	39 ± 10	12 ± 7	713%
K (meq/100g)	0.30 ± 0.19	0.19 ± 0.11	0.18 ± 0.09	30.0%
Ca (meq/100g)	2.92 ± 1.57	1.81 ± 0.71	1.83 ± 0.91	50.3%
Mg (meq/100g)	0.84 ± 0.59	0.53 ± 0.26	0.62 ± 0.50	148%
Na (meq/100g)	0.13 ± 0.04	0.14 ± 0.04	0.14 ± 0.03	18.2%
S (mg/kg)	13.1 ± 11.3	15.8 ± 9.2	18.8 ± 12.2	128%

Table 1.3 continued

Al (meq/100g)	1.46 ± 0.94	2.40 ± 1.06	2.35 ± 1.41	53.4%
Fe (mg/kg)	319 ± 181	166 ± 99	115 ± 94	48.1%
Mn (mg/kg)	37 ± 33	20 ± 16	19 ± 16	73.6%
Cu (mg/kg)	2.5 ± 0.7	2.3 ± 0.5	2.3 ± 0.5	24.1%
Zn (mg/kg)	2.5 ± 1.6	1.7 ± 0.6	1.8 ± 0.6	48.3%
B (mg/kg)	0.11 ± 0.07	0.11 ± 0.11	0.09 ± 0.06	85.2%

Mean Percent Error (MPE) reflects the accuracy of the FSM method at the study site, and varied widely by soil property (Table 1.3). Errors for texture and pH were relatively low, followed by Na, K, Cu and OC. Exchangeable P showed the largest percent error (MPE = 713%). Differences in variance between soil properties within the study site explain 37.5% of the variation in MPE values, with less variable soil properties resulting in lower mean percent error during mapping. The remaining variation in MPE values can be in part be attributed to inherent differences in the nature of the relationship between different soil property distributions and topography.

Management zones each contain 9-23 harvesting units, each 10-65 hectares in size, which provided the individual yield points for the plantation (Table 1.2). A large amount of variability in yield existed among harvesting units within management zones (Table 1.4) despite uniform management, planting material and planting date within a management zone.

Table 1.4 Mean, maximum, and minimum for oil palm yield in tons/ha for management zones (MZ) 1-6 in years 2013-2016.

Statistic	Management zone					
	1	2	3	4	5	6
Mean	13.3	13.7	11.1	18.7	18.7	17.1
Maximum	20.0	18.7	13.3	24.3	21.9	18.7
Minimum	5.8	10.6	8.5	13.0	17.0	15.1

1.5.1 Correlation of Yield with Soil Properties

No chemical or textural soil property as modeled by the FSM method (Ashtekar et al, 2014) was correlated with yield in more than two management zones (Table 1.5). While both the terrain algorithm data and the soil property data from the Functional Soil Maps used for correlation analysis are 30x30m raster layers of equal dimensions, the values of the soils properties modeled via the FSM method rely on 144 georeferenced soil analyses (Ashtekar et al, 2014), and so rely on an input data layer of lower data density than the SRTM Digital Elevation Model used in the terrain algorithm modeling.

Table 1.5 Soil texture and chemical properties correlation with oil palm yield for each Management Zone (MZ). Texture and Organic Carbon (OC) are reported as percentages, Al, ECEC, K, Mg and Ca are in meq/100g, and P, S, B and Cu are in mg/kg. Bold indicates significant correlation (P < 0.05).

	MZ 1		MZ 2		MZ 3		MZ 4		MZ 5		MZ 6	
	r	*P*-value	r	*P*-value	r	*P*-value	r	*P*-value	r	*P*-value	r	*P*-value
Sand	**-0.70**	**0.01**	-0.25	0.52	-0.10	0.77	-0.34	0.11	**0.68**	**0.05**	0.10	0.73
Clay	**0.70**	**0.01**	0.54	0.12	0.17	0.63	0.34	0.11	**-0.70**	**0.05**	-0.06	0.84
Silt	-0.40	0.19	**-0.80**	**0.01**	-0.48	0.15	0.12	0.57	-0.47	0.24	-0.11	0.71
OC	0.33	0.29	0.60	0.08	0.30	0.39	0.17	0.43	-0.05	0.91	0.16	0.59
pH	**-0.71**	**0.01**	**0.83**	**<0.001**	0.26	0.47	-0.14	0.52	0.49	0.22	0.10	0.74
Al	**0.70**	**0.01**	**-0.83**	**<0.001**	-0.40	0.24	-0.15	0.49	-0.32	0.45	-0.08	0.79
ECEC	-0.31	0.33	**0.82**	**<0.001**	0.24	0.51	-0.13	0.57	0.52	0.18	0.41	0.15
K	-0.42	0.18	-0.04	0.91	**-0.70**	**0.01**	0.25	0.26	-0.31	0.50	-0.15	0.62
P	-0.03	0.92	-0.49	0.18	-0.51	0.13	0.32	0.13	-0.05	0.91	0.26	0.36
Mg	0.41	0.19	0.31	0.41	0.54	0.10	-0.19	0.38	0.47	0.28	0.47	0.09
Ca	-0.55	0.07	0.48	0.18	-0.23	0.53	-0.09	0.67	0.44	0.31	**-0.7**	**0.004**
S	-0.52	0.09	**0.68**	**0.04**	-0.12	0.75	-0.38	0.08	**-0.74**	**0.04**	0.25	0.39
Fe	0.53	0.08	**-0.66**	**0.05**	0.10	0.79	0.37	0.08	0.43	0.32	-0.06	0.83
B	-0.48	0.11	0.07	0.86	0.15	0.67	0.08	0.71	0.60	0.14	-0.51	0.06
Cu	0.41	0.18	**0.83**	**0.004**	0.15	0.68	-0.09	0.68	-0.16	0.73	**0.63**	**0.01**
Mn	-0.25	0.43	0.12	0.75	-0.41	0.23	-0.29	0.18	**-0.77**	**0.03**	-0.44	0.12
Zn	0.10	0.75	-0.26	0.49	0.35	0.31	0.06	0.79	0.37	0.41	0.44	0.11
Na	0.08	0.81	0.61	0.07	-0.30	0.39	-0.33	0.12	-0.46	0.29	0.41	0.14

Modified Catchment Area had the most frequent and best correlation with oil palm yield across the plantation of any terrain algorithm (Table 1.6), with a significant correlation found in 4 of 6 management zones. However, the direction of the correlation differed among zones, with a positive correlation between MCA value and yield in MZ1 ($r = 0.86$) but negative correlations in MZ 2, 3, and 5 ($r = -0.88$, -0.79 and -0.87, respectively). The correlation of TWI and yield generally mirrored that of MCA, which is expected as both are means of predicting soil moisture from topography. However, TWI was not as often significant as MCA. Normalized height (NH) was positively correlated with yield in MZ 2 and 3 ($r = 0.77$ and 0.74, respectively). This is expected given that a high NH value indicates a high topographic position and would thus likely also indicate a predominantly dry grid cell. A negative correlation was found between NH and yield in MZ 4 ($r =-0.47$). A layer of large alluvial rocks was found to impede palm root development in topographically low areas of MZ 4, which did not occur in any other management zone, and may explain the negative correlation between NH and yield in this management zone.

Table 1.6 Correlation of terrain algorithms derived from SRTM DEM with oil palm yield for each Management Zone (MZ). Modified Catchment Area (MCA) and Topographical Wetness Index (TWI) are topographically-derived soil moisture indices, with higher values indicating a greater propensity to accumulate soil water. Normalized Height (NH) is relative terrain elevation after normalizing to the mean elevation of the target site. MCA, TWI and NH are relative measures and are unitless, while Slope is percent change in elevation for every unit change in horizontal distance. Bolded values indicate significant correlations (P < 0.05).

	MZ 1		MZ 2		MZ 3		MZ 4		MZ 5		MZ 6	
	r	*P*-value	r	*P*-value	r	*P*-value	r	*P*-value	r	*P*-value	r	*P*-value
MCA	**0.86**	**<0.001**	**-0.88**	**<0.001**	**-0.79**	**0.004**	0.11	0.61	**-0.87**	**<0.001**	0.30	0.29
TWI	**0.78**	**0.003**	**-0.80**	**0.01**	-0.55	0.09	0.13	0.57	-0.53	0.17	0.14	0.63
NH	-0.41	0.18	**0.77**	**0.01**	**0.74**	**0.01**	**-0.47**	**0.02**	-0.50	0.21	-0.19	0.51
Slope	-0.54	0.07	0.10	0.80	0.25	0.47	-0.18	0.41	0.10	0.82	0.15	0.61

The Modified Catchment Area (MCA) algorithm output provides a measure of the propensity of a grid cell to accumulate soil moisture, not a direct measure of soil moisture content. In order to compare the output of the algorithm with a direct measure of soil moisture content, depth to water table was recorded at the grid cell with highest and lowest MCA values in each management zone. These grid cells indicate the locations predicted by the MCA terrain algorithm to be the wettest and driest planted areas (i.e. with highest and lowest MCA values, respectively) for each management zone (Figure 1.3). Three readings were taken at each location during the height of the 2017 rainy season, during the months of May and June. Precipitation in the Piedmont region of the Llanos during the rainy season is characterized by brief but intense periods of rainfall, often lasting less than an hour, interspersed by clear skies, with average cumulative monthly precipitation reaching 500 mm (Marin and Ramirez, 2006). Readings were taken simultaneously at each location immediately following one hour after the end of five separate rain events by using a 10 cm diameter auger to bore a hole to the water table and recording depth from the soil surface. Modified Catchment Area predictions within each management zone were consistent with measured average depth to water table at the predicted driest and wettest grid cells in that grid cells predicted to be most prone to water accumulation within each management zone all had substantially shallower water tables and those predicted to be drier had lower average depth to water table measurements (Table 1.7).

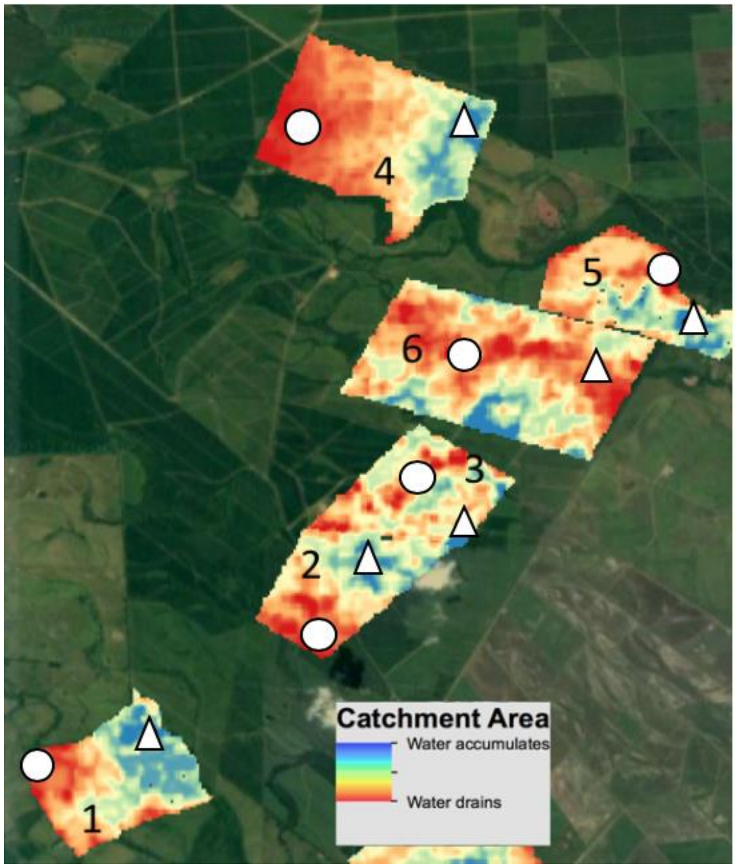

Figure 1.3 Modified Catchment Area by Management Zone, sampled at the wettest and driest planted grid cells in each management zone (marked respectively by triangles and ovals). Blue indicates high MCA values/ high propensity for soil moisture accumulation.

Table 1.7 Average depth to water table (DWT) and standard deviation in cm at grid cells with driest and wettest Modified Catchment Area (MCA) values within each management zone (MZ). MCA is unitless, with higher values indicating a relatively higher propensity to accumulate soil moisture.

	Driest		Wettest	
MZ	DWT, cm	MCA	DWT, cm	MCA
1	127±5	22	35±2	99
2	45±4	18	7±1	52
3	42±5	21	4±0.5	35
4	39±3	17	7±1	70
5	73±2	22	35±2	41
6	47±3	38	36±3	55

The negative correlation coefficient between MCA and yield in MZ 2, 3 and 5 (Table 1.6) indicates that a higher propensity for soil moisture accumulation reduced palm oil production in these management zones. Palm oil is susceptible to yield loss under waterlogged conditions (Lee and Ong, 2006; Henson et al, 2008), so the elevated potential for waterlogging in grid cells with high MCA values was a likely mechanism behind the negative correlation seen in the data. The relationship between MCA and palm oil yield was very different in MZ 1 than in MZ 2, 3 and 5, showing a positive correlation between yield and MCA ($r = 0.86$). The positive correlation between palm oil yield and MCA in MZ 1 might indicate this part of the plantation is excessively well drained, with oil palms in grid cells with lower MCA values suffering yield losses from insufficient soil moisture (Paramanthan, 2000). Yield in MZ 1 was negatively correlated to sand ($r = -0.7$), which may support the argument that insufficient moisture is driving yield differences within this management zone. Indeed, the depth to water table at the grid cell with the lowest MCA value was 127cm, compared to 45, 42, and 73cm at the grid cells with lowest MCA values in MZ 2, 3 and 5 (Table 1.7). Management Zone 1 protrudes out of the southwestern end of the plantation, and the harvesting units at the most southwestern edge are surrounded on three sides by a sharp drop to lower-lying terrain outside the plantation's boundaries, potentially creating an excessively well-drained zone at the management zone's edge. As seen on Figure 1.4, it is the harvesting units at this edge that have the lowest MCA values and the lowest yields.

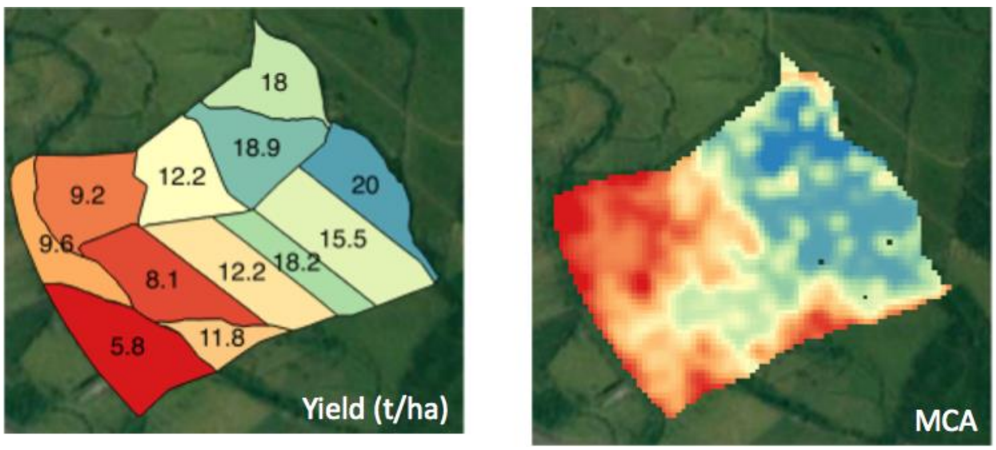

Figure 1.4 Yield in t/ha of fresh fruit bunches and Modified Catchment Area (MCA) for Management Zone 1. Blue indicates a higher yield in the left-hand image and a higher MCA value/greater propensity for soil moisture gain in the right-hand image. Management Zone 1 comprises 306ha.

Most of the land in MZ 6 with high MCA values lies at the southern edge of this management zone and had originally been deemed too wet for oil palm production and was left unplanted. As can be seen in Figure 1.5, the planted areas lie along a ridge of well-drained terrain directly between two poorly-drained sectors. The planted grid cells thus registered similar MCA values, with a range of 38-55 on a normalized scale of 1-100. A relative homogeneity in soil moisture might explain why there was no significant correlation between MCA and yield for this management zone. Management Zone 4 had a wide range of MCA values (38-70), yet no significant correlation between MCA and yield was found for this area. An extensive deposit of large alluvial rocks near the soil surface across a large portion of this area seemed on visual inspection to have hindered palm root growth in affected areas and may have introduced an extraneous factor that obscured the effect of variable soil hydrology on palm oil yield.

The management zones where no correlation was found between yield and soil moisture were planted earlier than the others. Management Zones 4 and 6 were planted in 1990 and 1999, respectively, while MZ 1, 2, 3 and 5 were planted 2004-5. It is thus possible that the age of the stand may play a role in determining the relationship between oil palm yield and soil moisture.

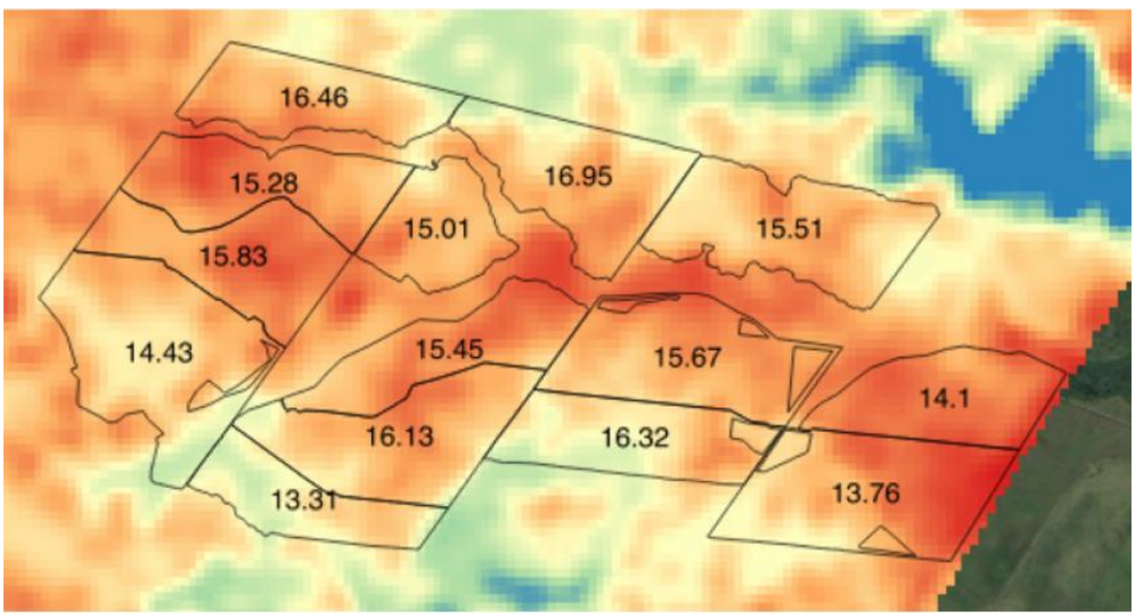

Figure 1.5 Yield in t/ha of fresh fruit bunches over Modified Catchment Area (MCA) map for Management Zone 6, where blue indicates a higher MCA value/greater propensity for soil moisture gain. Management Zone 1 comprises 410ha.

1.6 Discussion

1.6.1 SRTM DEM as the Basis for Topographic Analysis in Llanos Oil Palm

An average percent change by grid cell of 2.0% between the SRTM and ASTER DEM's for the target site is within the range of average percent values reported in previous comparisons of SRTM and ASTER Global DEM's (Fig. 1.2), although previous studies have mostly focused on mountainous locations with more variable topography (Arabelos, 2000; Nikolakopoulus et al., 2006). This indicates that the two DEM's, though constructed via very different methods- interferometric synthetic aperture radar and the use of stereoscopic VNIR images, respectively- present a consistent model for capturing elevation at the target site. Given how these methods are affected differently by atmospheric and ground cover distortions, their consistency in providing similar elevation readings can be interpreted as evidence of their reliability (Arabelos, 2000; Nikolakopoulus et al., 2006;). This initial assessment of the reliability of the global SRTM and ASTER DEM's for topographic analysis of Llanos oil palm plantations is thus an important conclusion, for use of these DEMs offer oil palm managers a low-cost alternative for measuring topography across their plantations and for performing any subsequent topographic analysis.

1.6.2 Continuous Soil Property Mapping

The Mean Percent Error (MPE) of the soil property predictions made with the FSM soil property distribution model (Ashtekar et al., 2014) varied widely across soil properties. The MPE of pH was lowest (3.2%), followed by soil texture values (sand 9.2%, silt 6.3%, clay 12.5%) (Figs. 1.6-1.7). The low mean error for pH can largely be explained by the very low variability in pH throughout the plantation (S.D. = 0.1-0.2). However, soil texture showed significant variation, with each particle size displaying a variance of approximately 22 percentage points around their respective means. Given the collinearity of sand, silt and clay percent values, their corresponding variances are codetermined. The distribution of soil texture in an alluvial soil is intimately linked to topography, as particles of different size can be deposited and redistributed by water along a topographic gradient. Mapping texture in alluvial soils is difficult because the particle size in the soil is related to the energy of the river when it was deposited. Sand is deposited near the river whereas silt and clay further from the river source (Lyon and Buckman, 1922). Some of the higher sandier places may be old natural levees. Subsequent influences by other soil forming factors, including human action, are less likely to impact soil texture than properties such as organic matter and nutrient concentrations. It might therefore be expected that a soil property mapping model based on capturing the relationship between topography and soil property distribution would display a lower mean error in predicting soil texture values relative to other properties, as is the case in this study site.

Organic carbon has complex interactions with surrounding organisms, affecting and being affected by microbial and plant processes (Schmidt, 2011) and these interactions by in turn be affected by topography in complex ways that may be more difficult to capture than the movement of particles of various sizes across a gradient, leading to increased error in the FSM model relative to soil texture (OC MPE = 33%) (Figure 1.6). However, after controlling for temperature, water content is understood to be the most important factor, affecting oxidation and CO_2 production in soils via the determination of air-filled pore space (Makiranta et al., 2009; Berglund and Berglund, 2011; Renou-Wilson et al., 2014), and soil water movement is gravity driven and thus largely controlled by topographic gradients, so a direct mechanism exists for topography to drive field scale variability in soil carbon (Renou-Wilson et al., 2014). Accordingly, within the plantation higher soil carbon content was associated with topographic low-spots with near-zero slopes. These areas can exhibit high water accumulation and poor drainage, which can in turn reduce available pore space for gas exchange and inhibit aerobic CO_2 respiration, leading to the accumulation of soil carbon (Berglund and Berglund, 2011). Functional Soil Mapping appears to have captured this relationship within the study site, which in turn explains the degree to which it successfully predicted OC values.

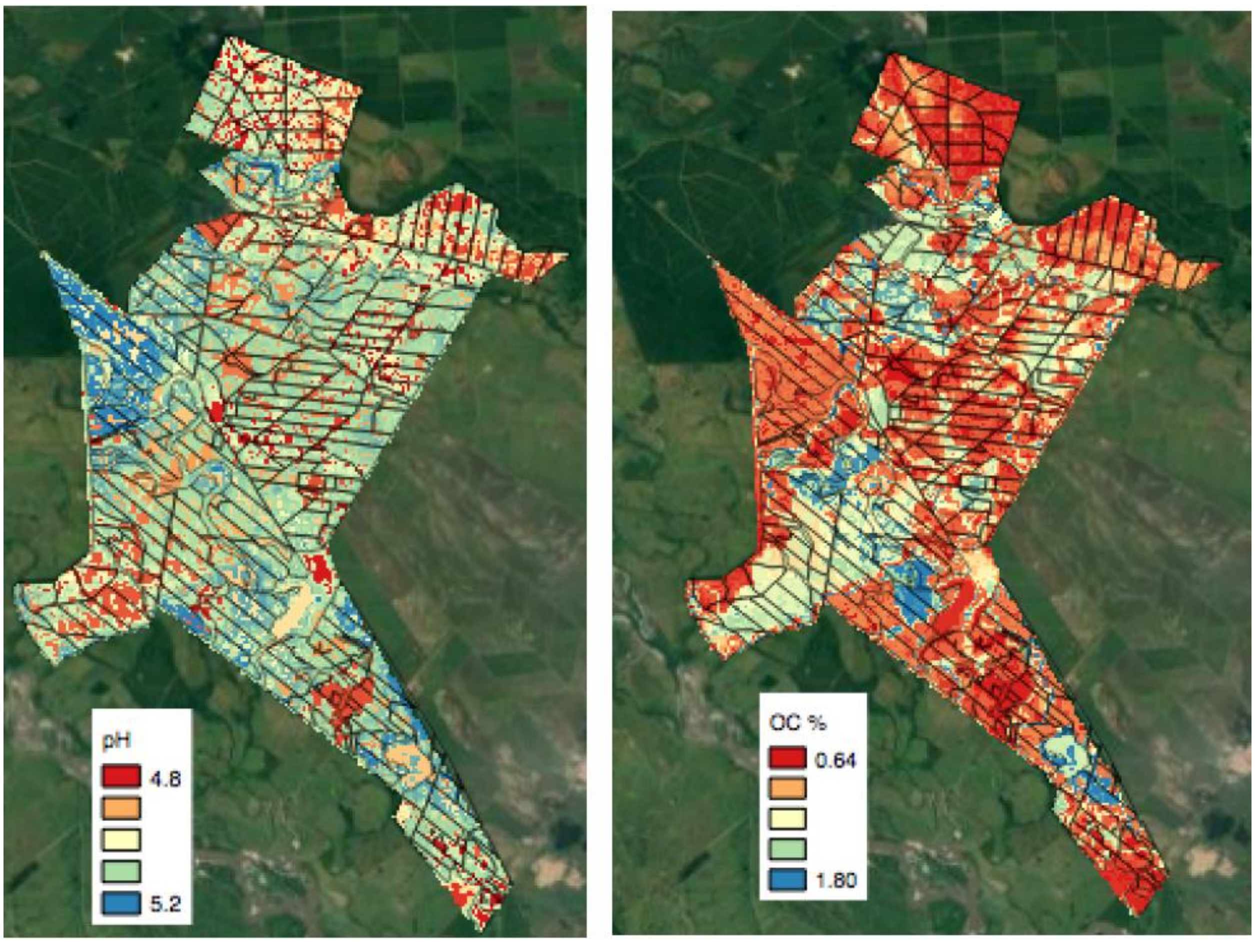

Figure 1.6 Continuous soil maps of pH and organic carbon (OC%) at 0-20 cm at 30x30m resolution. Soil property distributions were modeled according to "Functional Soil Mapping" method (Ashtekar and Owens, 2013; Ashtekar et al., 2014), whereby topography is assumed to be the driver of soil variability at the field scale.

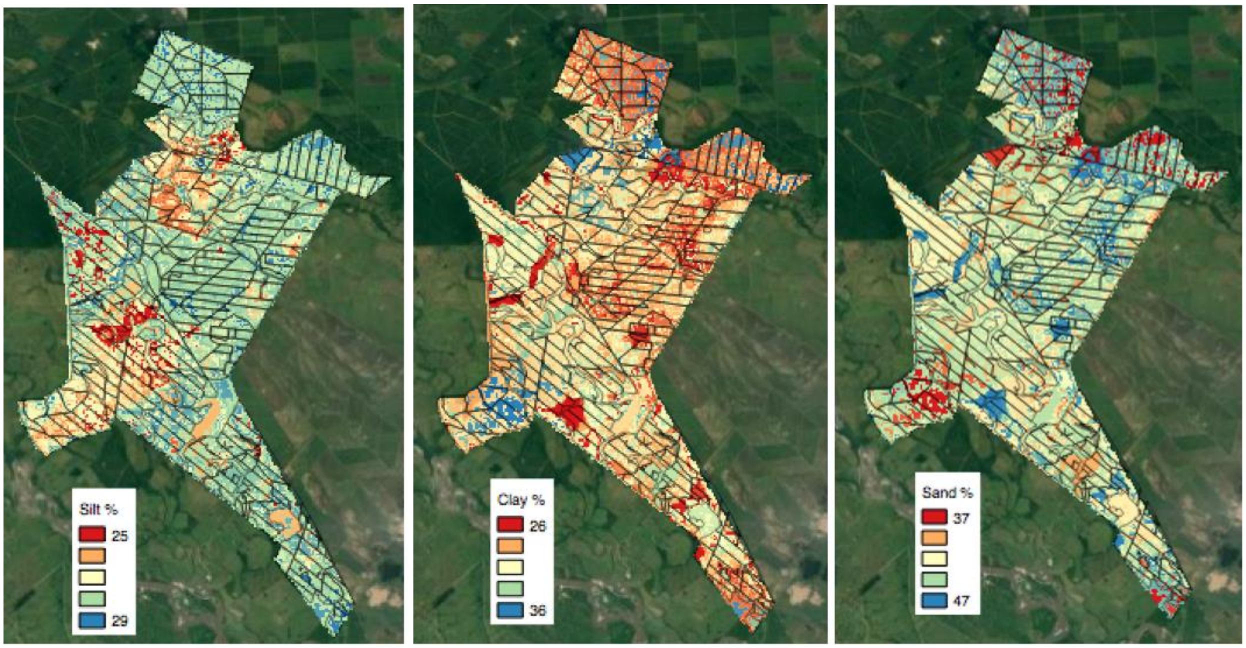

Figure 1.7 Continuous soil maps of percent clay, silt and sand at 0-20 cm at 30x30m resolution. Soil property distributions were modeled according to "Functional Soil Mapping" method (Ashtekar and Owens, 2013; Ashtekar et al., 2014), whereby topography is assumed to be the driver of soil variability at the field scale.

Potassium and P are both added to the soil in large amounts as part of fertilizer applications, yet the MPE for both properties were significantly different (MPE K =30%, P = 713%). As a monovalent cation in a low ECEC soil under high rainfall conditions, soil K is likely to be leached from the soil profile and be carried by water movement along the topographic gradient (Etchevers et al., 2005). Its distribution throughout the plantation may thus be strongly determined by the topographic gradient. The Functional Soil Mapping model correspondingly shows higher concentrations of soil K in low topographic positions with poor drainage (Figure 1.8). However, applied P is likely to be immobile, and Llanos soils have high concentrations of aluminum- and iron-oxides with a high potential for fixation of P via ligand-exchange reactions (Goosen, 1971; Parfit, 1977). As such, applied P is unlikely to be redistributed along the topographic gradient, and topographic variability is unlikely to explain variability in soil exchangeable P, as seen in this study site.

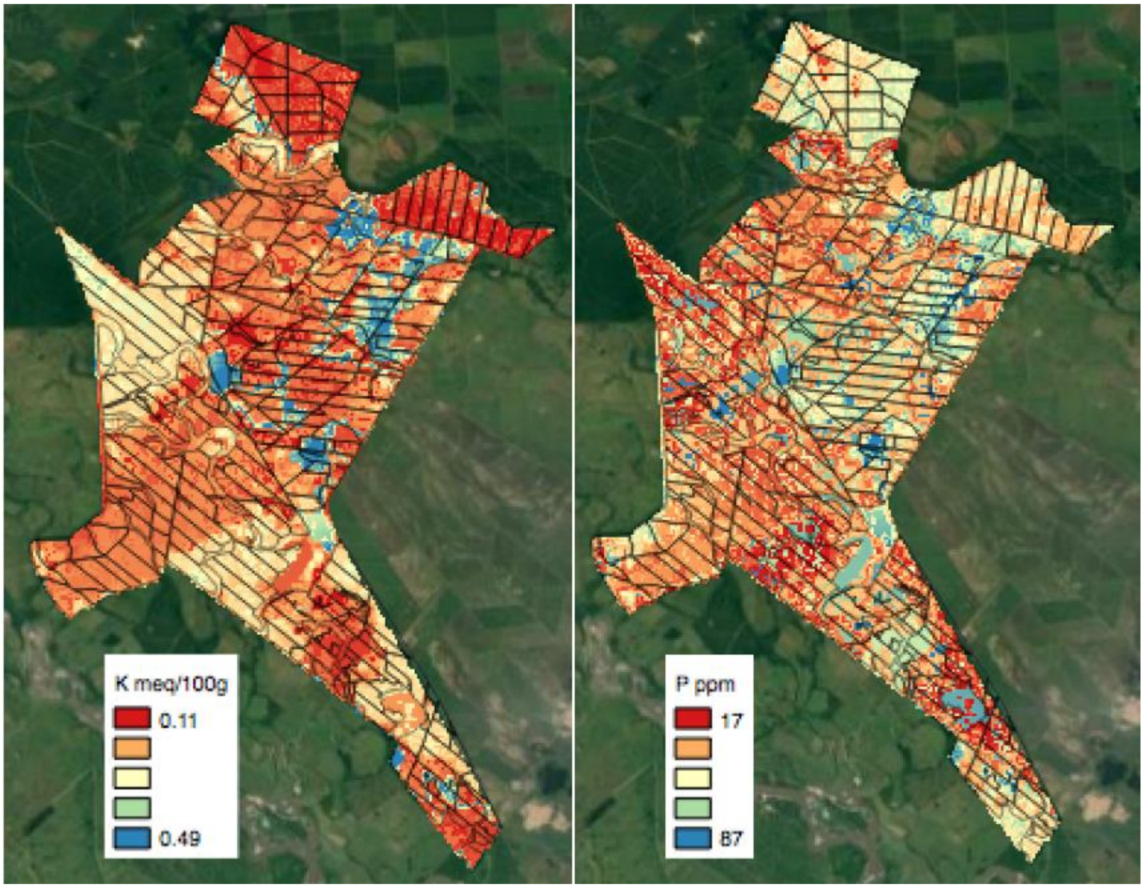

Figure 1.8 Continual soil property maps of soil K (meq/100g) and P (ppm or mg/kg) at 0-20cm depth using the Functional Soil Mapping method.

1.6.3 Soil Property Distribution as an Explanatory Factor for Yield Variability

Both the correlation analysis of individual soil properties with average yields and the regression analysis of yield on MCA suggests that yield variability in the target site is highly related to variability in soil moisture distribution (Figure 1.9). Yield in MZ 1, 2, 3 and 5 showed a consistent correlation with MCA values, while the management zone with the most consistent MCA across harvest units, zone 6, showed the least amount of yield variability. Large segments of MZ 4 contain large alluvial rocks deposited near the surface, which present an uncontrolled for variable that may have impacted yield variability. In this study site, MCA as a predictor of soil moisture was both positively and negatively correlated with yield across different management zones, suggesting the potential for both excess and insufficient soil moisture to act as limiting factors to oil palm fresh fruit bunch production. The Llanos region of Colombia is an area of high rainfall, particularly in the Piedmont region of the study site, where annual rainfall can reach 4000 mm (IGAC, 2014). The topographic layout of the study site, with relative topographic highs and lows spread throughout the plantation, can thus result in the rapid redistribution of large amounts of water by gravitational pull following rain events, leading to zones of disparate levels of soil moisture within close proximity (Zhang, 2004). Additionally, the marked seasonality of rainfall in the region means that palms can be exposed to very limited rainfall in the dry season followed by intense precipitation in the wet season, creating the potential for hydraulic stress from both excessive and insufficient soil moisture at different times of the year, and suggesting that the ideal soil drainage class for oil palm in the plantation would balance draining excessive moisture in the wet season with the retention of sufficient moisture in the dry season (Jipp et al., 1998). Oil palm is highly susceptible to decreased agronomic function following both excessive and insufficient soil moisture, and achieving adequate drainage is imperative for achieving maximum yields (Fedepalma, 2016)**.** Oil palm grows in areas of intensive solar radiation and can exhibit high photosynthetic activity and respiration rates (Fedepalma, 2016). Oil palm production is thus only possible in areas of high precipitation (minimum 2000-2500 mm) (Pirker et al., 2016), as transpiration rates of up to 280-350 mm/palm/day are required to maintain optimal plant function (Carr, 2011). Sustaining such high transpiration levels requires constant replenishing of soil moisture, and sustained stress from insufficient soil moisture can lead to sharp drops in palm oil production (Pirker et al, 2016). However, oil palm cannot grow under saturated soil conditions, as its root system is ill-adapted to waterlogged conditions (Carr, 2011; Pirker et al, 2016). Proper drainage is therefore required to evacuate excess water. Under the intense precipitation of the Llanos rainy season, poor drainage can lead to sustained waterlogged conditions and negatively affect yield. Given these factors, the effects of drainage of oil palm conditions can be pronounced, explaining the apparent high explanatory power of MCA terrain analysis on variability in oil palm yield across the target site.

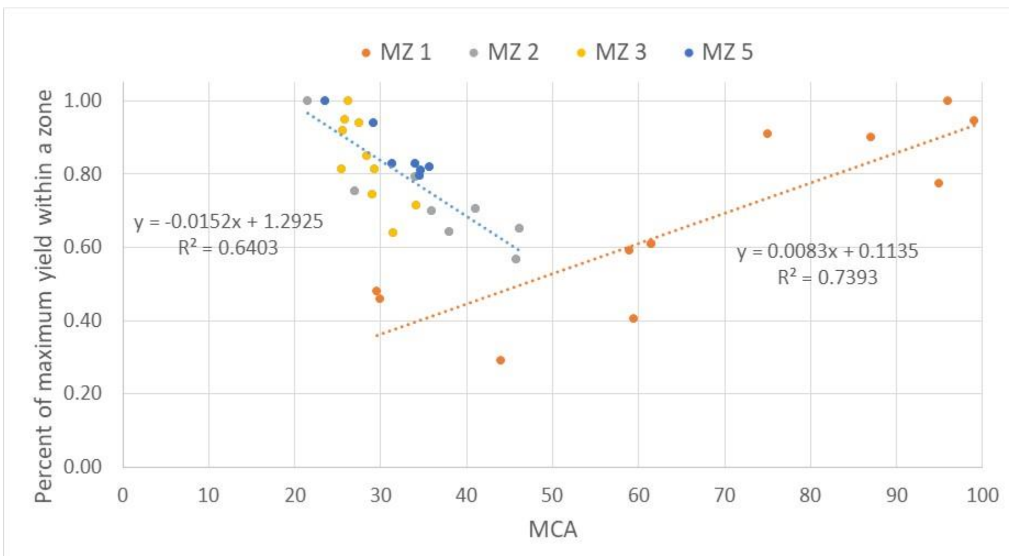

Figure 1.9 Normalized yield plotted against Modified Catchment Area (MCA) for management zones (MZ) with a statistically significant correlation between yield and MCA values.

The absence of any consistent correlation between soil physical and chemical properties may potentially be explained by the fact that few grid cells contained soil property values outside of the critical range for oil palm production at all depths of sampling (Table 1.8), as determined by the Colombian Nacional Research Center for Oil Palm (Cenipalma), the research arm of the

Colombian Nacional Federation of Oil Palm Growers (Fedepalma, 2016)**.** In this plantation compound fertilizer has been applied with a nutrient ratio in accordance to general Fedepalma recommendations (Fedepalma, 2016), so it is possible that no individual macronutrient would be sufficiently deficient for soil property distribution values to register a significant decline in yield. Boron deficiency is sometimes seen in Llanos oil palm (Fedepalma, 2016) and visual symptoms of B deficiency were spotted in the plantation, but these were localized to a few isolated stands of palm, and any associated decrease in yield would not have been likely to significantly affect yield data at the dimension of the harvesting unit. Any direct correlation between soil chemical and soil property values may have been obscured by the strong influence of variability in soil water and yield distribution, and not detectable from the current data.

Table 1.8 Soil analysis values considered optimal for oil palm production. Extraction methods used were Bray II for extractable P, ammonium acetate for K, Ca, Mg and Na, Mehlich III for minor elements, and KCl for exchangeable Al, following Fedepalma criteria (Fedepalma, 2016).

		Low	High
pH		4.5	5.5
E.C.	ds/m	2	4
O.M.	%	2	4
CEC	meq/100g	10	20
P	ppm	15	20
K	meq/100g	0.2	0.4
Mg	meq/100g	0.2	0.3
S	ppm	10	15
B	ppm	0.25	0.5
Fe	ppm	15	30
Cu	ppm	0.5	1.5
Mn	ppm	5	10
Zn	ppm	1	2

1.6.4 Conclusions and Further Research

The limiting factor to this study's ability to evaluate the effect of soil property values on yield variability across the study site was the large size of the harvesting units relative to the DEM-based grid cells. This disparity in data layer dimensions resulted in the lowering of the dimensionality of the data matrix based on the soil property raster layers and meant that the yield variability within the harvesting units could not be evaluated with respect to corresponding soil property values. The manual harvesting required in oil palm production precludes the use of yield monitors capable of gathering high precision yield maps, but an effort to reduce the size of harvesting units in similar further studies would greatly increase the statistical power of subsequent analyses of the relationship between soil property distributions and yield variability

Given the apparent importance of soil moisture in understanding yield variability across the plantation, future studies could further explore the distribution of soil properties related to soil hydrology. MCA values provide a measure of the propensity of a grid cell to lose or accumulate water, but do not provide a direct measure of soil moisture content. Measuring soil moisture tension at specified time intervals at grid cells of varying MCA values would allow for establishing a direct relationship between MCA and soil moisture (Davidson, 1965; Schertmann 1978). Additionally, mapping of soil bulk density and hydraulic conductivity may reveal additional drivers of soil moisture variability within the study site that act in concert with the topographic gradient to control the movement and retention of soil moisture (Blake and Hartge, 1986; Klute and Dirksen, 1986). Since yearly precipitation patterns can vary significantly in the Llanos (IGAC, 2014), soil moisture readings may vary significantly across years. Understanding the relationship of soil moisture across a plantation with fluctuations in yearly precipitation may offer a means of understanding an important aspect of temporal fluctuations in oil palm yield, a topic of perennial concern for palm growers (Fedepalma, 2016).

Developing methods to model soil properties across an oil palm plantation that can provide relevant information for plantation managers while fitting within their budgetary and operational constraints is an important first step making improvements in plantation management, particularly fertilizer management that can generate an economic benefit to growers. This paper is meant to present an initial approach towards that goal. Subsequent chapters in this dissertation will delve into how these digital soil mapping methods can be linked to fertilizer management strategies, and how these affect the economic performance of an oil palm production system in the Colombian Llanos.

1.7 References

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CHAPTER 2. ESTIMATING THE FINANCIAL RETURNS OF IMPROVED YIELD RETURNS TO FERTILIZER

2.1 Abstract

Oil palm (*Elaeis guineensis* Jacq.) plantations in the Colombian Llanos face strong pressure to increase their yield returns on fertilizer to improve their financial performance. As fertilizer is one of their largest recurrent costs of production, marginal changes in yield returns on fertilizer can have large impacts on discounted costs and net discounted benefits from palm oil production (Svatonova et al., 2015). Given the difficulty in matching individual fertilizer applications to yield response in oil palm (Corley and Tinker, 2016), the relationship between yield response to fertilizer and plantation financial performance can be better understood through a cashflow analysis of the twenty-five-year production cycle. A spreadsheet model was used to establish a baseline financial assessment of oil palm production in the Llanos, using data from a plantation in Casanare as a case study. The impact on net present value (NPV) from a one percent improvement in yield returns to fertilizer was calculated and used to evaluate the sensitivity of oil palm financial performance to marginal changes in yield return to fertilizer (Powell and Baker, 2009). This sensitivity analysis was performed for a one percent improvement in yield returns stemming from a removal of excess fertilizer without impacting yields, and from increasing yield from reallocating monetary resources for fertilizer across areas of the plantation or across nutrients to improve yield response given the same level of spending on fertilizer. Monte Carlo simulation was used to evaluate the impact of variability in oil palm fresh fruit bunch (FFB) value and fertilizer price on NPV. Cashflow analysis revealed an expected NPV of $846.87 per hectare for a 25-year cycle of oil palm production before accounting for the cost of land, with a standard deviation of $410.75 resulting from fertilizer and palm FFB price

uncertainty. A 4.68% and 14.46% increase in the plantation's expected NPV resulted from a one percent increase in yield return on fertilizer, respectively from reduction of excess fertilizer and reallocation of current resources within the plantation. Furthermore, breakeven analysis was used to determine how unintended yield reductions from changes in fertilizer management might affect the financial impact of changes in fertilizer management (Markham and Palocsay, 2006). A yield loss of 0.32% was sufficient to eliminate the savings from a 1% reduction in fertilize use at current input and output prices, highlighting the risks of arbitrary reductions in fertilizer applications.

2.2 Introduction

Fertilizer costs are one of the largest expenses incurred in the production of palm oil, accounting for approximately one-third of all recurring expenses after an oil palm stand (*Elaeis guineensis* Jacq.) has been established (Fedepalma, 2016). Because oil palm yield response to fertilizer application varies widely both across and within plantations (Woittiez et al., 2017), the returns associated with this expense can also be highly variable and represent a large source of uncertainty when calculating net income over the twenty-five-year productive cycle of an oil palm stand. Oil palm production requires large up-front investments that can tie down producers for the duration of the crop's production cycle and necessitate continual expenses to maintain the stand even during years of adverse market conditions (Tinker, 1984). Unlike producers of other oilseeds like soybeans and canola, who can reduce or increase acreage planted on an annual basis (Chavas and Holt, 1990), oil palm producers seeking to reduce costs in response to short-term pressures must attempt to cut present operational expenses without impairing the plantation's future productive potential (Tinker, 1984). Plantations facing liquidity crises thus often resort to reductions in fertilizer applications as a means of alleviating short-term pressures on their annual operating budgets (Corley and Tinker, 2016; Fedepalma, 2016). However, such measures can often generate larger losses in future yields than the value of the fertilizer saved, and trap plantations in a downward cycle of declining productivity and a subsequent inability to cover the costs of fertilizing necessary to generate future production. This practice is particularly prevalent amongst plantations in the Colombian Llanos, where stagnant domestic market compounded by high input costs associated with the high transport costs of bringing freight into the Llanos has reduced the economic viability of oil palm production and forced existing plantations to reduce expenses in the short-term at the expense of long-term yield potential (Fedepalma, 2016; Perfetti del Corral, 2018).

Thus facing continued pressure to reduce costs while minimizing the adverse impact on future yields, there is significant interest within the oil palm industry in the Llanos in developing methods for improving yield returns to fertilizer, measured as the quantity of oil palm fresh fruit bunch (FFB) production per every kilogram of nutrient applied (Fedepalma, 2016). Because of oil palm's continual production of FFB's throughout its lifetime and complex internal feedback mechanisms within the palms affecting the timing of production, matching fertilizer applications from a given year to specific harvests is highly uncertain, making it difficult to meaningfully interpret yield response to fertilizer on a yearly basis (Tinker, 1984; Goh and Po, 2005). To produce a more accurate assessment of the financial impact of yield returns to fertilizer on palm oil production in the Llanos, cashflow from a plantation's operations can be examined over a twenty-five-year production cycle, and the impact on key measures of plantation financial performance from a change in yield returns to fertilizer can be assessed.

The goal of this paper is to estimate the financial effects of improving yield returns to fertilizer in the Llanos. Using the financial analysis of a target plantation near Villanueva, Casanare as the baseline “without” case in a cost benefit analysis, a spreadsheet model was used to perform a sensitivity analysis and test the effect on net present value (NPV) (Powell and Baker, 2009). This improvement in yield returns to fertilizer will be modeled as arising in two different ways, both from reducing excess fertilizer such that no yield loss results, and by reallocating monetary resources for fertilizer applications to achieve a higher overall use efficiency. In this second case, reallocation of resources for fertilizer application covers both the possibility of reallocating fertilizer from areas in the plantation with a lower marginal yield response to areas with a higher marginal yield response, and of substituting one nutrient for its monetary equivalent amount of a different nutrient such that the overall marginal yield response to fertilizer application is increased (Corley and Tinker, 2016; Martinez, 2018b). Monte Carlo simulation is used to account for variability in fertilizer and oil palm prices (Mun, 2006). To account for the inherent uncertainty in predicting yield responses to changes in fertilizer applications, breakeven analysis is used to determine the percent overall loss in yield that would be needed for the plantation to experience a negative change in net income from the change in fertilizer management (Markham and Palocsay, 2006). In doing so this paper also seeks to explore the risk faced by plantations of changing fertilizer management with the purpose of improving yield returns to fertilizer, and to examine how the nature of risk changes when improvements in yield returns to fertilizer are sought by removing excess fertilizer versus by reallocating current spending on fertilizer to increase the yield obtained from current resources.

2.3 Methods

2.3.1 Plantation Practices and Costs

The study site was a 5,220 hectare oil palm plantation in the Colombian Llanos, in the municipality of Villanueva, Casanare. Management practices and input applications were identical throughout the plantation and followed best practices as defined by the Colombian National Federation of Palm Oil Growers (Fedepalma, 2016). Palms received uniform applications of premixed 13-5-27-5 (N-P-K-Mg) fertilizer at the rate of 4 kg/palm from the onset of production, for a total yearly per hectare application of 83 kg/ha N, 32 kg/ha P, 173 kg/ha K, and 32 kg/ha Mg. The fertilizer was a physical mixture of urea, monoammonium-phosphate, muriate of potash, and magnesium oxide.

Costs were divided into the initial capital costs of establishing an oil palm stand and recurrent yearly costs, expressed on a per hectare basis (Tables 2.1 and 2.2). The capital costs consisted of the prenursery and nursery establishment, clearing of the previous crop, planting, infrastructure repair (including plantations roads and drainage ditches), and the costs of machinery and equipment needed for land clearing and planting. Given the instability of land prices in the Llanos and the fact that the plantation has owned the land since well before the current production cycle, the price of the land was not included in the model as a cost (Svatonova et al., 2015). Recurrent costs were comprised primarily of fertilizer and harvesting costs, followed by the lesser expenses of weed control, phytosanitary control, pruning, administrative expenses, technical staff salaries, and other miscellaneous expenses. Weeding and pruning costs both varied by year, with weed control being more demanding with new plantings but decreasing as the palm canopy closes after the sixth year after planting (Svatonova et al., 2015). Conversely, pruning is least demanding in new plantings, with costs increasing until stabilizing after the sixth year (Svatonova et al., 2015). Baseline fertilizer costs were based on an average dose of 4 kg/palm of compound 13-5-27-5- fertilizer. Yearly farm-gate price was assumed to follow a PERT distribution with a minimum value of $520/ton, a mean of $600/ton, and a maximum of $680/ton, with no correlation between different years (Clark, 1962; Fedepalma, 2016). Following the plantation's practice, no fertilizer was applied on the last year of the palm's production cycle and applications were cut by half on the second-to-last year. Harvesting in oil palm is done manually by teams of contracted workers who are paid per kg of FFB's harvested. Harvesting costs are thus highly variable and are a function of yield. A rate of $0.022/kg of FFB was used to calculate harvesting costs from yearly yield values. Yearly FFB prices where assumed to follow a PERT distribution with a minimum of $0.08 /kg, a mean of $0.12 /kg, and a maximum of $0.16, drawn independently of fertilizer prices and with no correlation between different years (Fedepalma, 2016). Expected yield values used for financial analysis were calculated from historical averages within the plantation, with 20.4 ton/ha FFB as the average adult yield for the plantation. For new plantings yields increase with age and then stabilize after the eighth year. Yields and cost of production for the plantation were in line with expected FFB yields for similarly sized plantations in the Llanos (Fedepalma, 2016), and were converted to USD using an exchange rate of 2,800 COP per USD.

Table 2.1 Initial per hectare capital costs of oil palm production.

Prenursery establishment	$140.00
Nursery establishment	$150.00
Previous crop clearing	$450.00
Planting	$480.00
Infrastructure repair	$175.00
Machinery and Equipment	$320.00

Table 2.2 Recurrent per hectare costs in palm oil production.

Year	Fertilizer	Weed Control	Phytosanitary	Pruning	Administrative	Technical Staff	Maintenance	Harvest
1	$48.00	$167.04	$50.00	$0.00	$155.93	$47.41	$138.89	$0.00
2	$192.00	$156.30	$50.00	$23.70	$155.93	$47.41	$138.89	$0.00
3	$288.00	$106.67	$50.00	$26.30	$155.93	$47.41	$138.89	$127.04
4	$384.00	$106.67	$50.00	$48.15	$155.93	$47.41	$138.89	$339.63
5	$528.00	$94.81	$50.00	$47.41	$155.93	$47.41	$138.89	$424.81
6	$576.00	$92.22	$50.00	$47.41	$155.93	$47.41	$138.89	$414.07
Adult	$576.00	$90.74	$50.00	$47.41	$155.93	$47.41	$138.89	$568.15
Adult %	34.40%	5.42%	2.99%	2.83%	9.31%	2.83%	8.29%	33.93%

2.3.2 Financial Assessments

A discount rate of 10% was used in the model (Svatonova et al., 2015). Net Present Value (NPV) was used as a measure of the overall financial return of a complete twenty-five-year cycle of palm production (Brooks and Mukherjee, 2013; Svatonova et al., 2015), and was calculated according to the following equation:

Equation 1.

$$NPV = \sum_{t=1}^{T} \frac{NB_t}{(1+r)^t} = \sum_{t=1}^{T} \frac{B_t}{(1+r)^t} - \sum_{t=1}^{T} \frac{C_t}{(1+r)^t}$$

where net benefits (NB) for year t are the sum of all benefits from the project for that year minus the sum of all costs, discounted using a discount rate r. To account for uncertainty from price variability, the distribution of NPV was determined through one thousand iterations of the cashflow model (Mun, 2006). The @Risk add-on to Microsoft Excel was used to generate the Monte Carlo simulation within the spreadsheet model (Manual, 2002).

2.3.3 Sensitivity Analysis

Yield returns to fertilizer were computed as the ratio of yield in FFB to total kilograms of nutrient applied (Morris et al, 2018). To perform sensitivity analysis on the financial effect of improvements in yield returns to fertilizer for the plantation, yield returns to fertilizer were increased by 1%, both by 1) decreasing fertilizer use while assuming no yield loss, and by 2) increasing yield without increasing fertilizer applications. In each case, NPV was recalculated and the financial effect of improvements in yield returns to fertilizer from both fertilizer reduction and yield increase were computed for each of the three measures of project value by taking the difference between baseline scenario and both improved scenarios.

Equation 2.

$$NPV_{net} = NPV_{Improved} - NPV_{Baseline}$$

The robustness of expected improvements in yield returns to fertilizer was tested by using breakeven analysis to determine the percent yield loss from each management change in fertilizer use at which the average net NPV resulting from the management change is reduced to zero (Markham and Palocsay, 2006).

2.4 Results

The spreadsheet model of the twenty-five-year cycle of an oil palm stand (Table 2.3) revealed a per hectare NPV of USD $846.88, with a standard deviation of $410.75. Discounted total costs were estimated at $13,462 with a standard deviation of $46.06, while discounted benefits from FFB production was calculated at $14,309 with a standard deviation of $407.02 (Table 2.4). Costs and benefits were not evenly spread throughout the production cycle, with high initial costs and low production for the initial seven years after planting. Spending on fertilizer accounted for the largest share of discounted total costs, followed by spending on harvesting, respectively accounting for 29.5% and 21.5% of discounted total costs for the plantation across a twenty-five-year production cycle (Table 2.3).

Table 2.3 Cashflow analysis of palm oil production in the Llanos, using expected prices.

Year	Harvest	Fertilizer	Other Operational Costs	Total Costs	Benefits	Net Benefits	Fertilizer kg/palm	FFB ton/ha
0				$1,715.00		-$1,715.00		
1	$0.00	$47.52	$559.26	$606.78	$0.00	-$606.78	79.2	0
2	$0.00	$190.08	$572.22	$762.30	$0.00	-$762.30	316.8	0
3	$127.04	$285.12	$525.19	$937.34	$624.00	-$313.34	475.2	5.2
4	$339.63	$380.16	$547.04	$1,266.83	$876.00	-$390.83	633.6	7.3
5	$424.81	$522.72	$534.44	$1,481.98	$1,404.00	-$77.98	871.2	11.7
6	$414.07	$570.24	$531.85	$1,516.17	$1,824.00	$307.83	950.4	15.2
7	$380.22	$570.24	$530.37	$1,480.83	$2,088.00	$607.17	950.4	17.4
8	$432.67	$570.24	$530.37	$1,533.28	$2,376.00	$842.72	950.4	19.8
9	$445.78	$570.24	$530.37	$1,546.39	$2,448.00	$901.61	950.4	20.4
10	$445.78	$570.24	$530.37	$1,546.39	$2,448.00	$901.61	950.4	20.4
11	$445.78	$570.24	$530.37	$1,546.39	$2,448.00	$901.61	950.4	20.4
12	$445.78	$570.24	$530.37	$1,546.39	$2,448.00	$901.61	950.4	20.4
13	$445.78	$570.24	$530.37	$1,546.39	$2,448.00	$901.61	950.4	20.4
14	$445.78	$570.24	$530.37	$1,546.39	$2,448.00	$901.61	950.4	20.4
15	$445.78	$570.24	$530.37	$1,546.39	$2,448.00	$901.61	950.4	20.4
16	$445.78	$570.24	$530.37	$1,546.39	$2,448.00	$901.61	950.4	20.4
17	$445.78	$570.24	$530.37	$1,546.39	$2,448.00	$901.61	950.4	20.4
18	$445.78	$570.24	$530.37	$1,546.39	$2,448.00	$901.61	950.4	20.4
19	$445.78	$570.24	$530.37	$1,546.39	$2,448.00	$901.61	950.4	20.4
20	$445.78	$570.24	$530.37	$1,546.39	$2,448.00	$901.61	950.4	20.4
21	$445.78	$570.24	$530.37	$1,546.39	$2,448.00	$901.61	950.4	20.4
22	$445.78	$570.24	$530.37	$1,546.39	$2,448.00	$901.61	950.4	20.4
23	$445.78	$570.24	$530.37	$1,546.39	$2,448.00	$901.61	950.4	20.4
24	$445.78	$285.12	$530.37	$1,261.27	$2,448.00	$1,186.73	950.4	20.4
25	$445.78	$0.00	$530.37	$976.15	$2,448.00	$1,471.85	950.4	20.4

Yield returns to fertilizer throughout the life of the oil palm stand were 3.14 kg FFB/kg of nutrient. When a 1% increase in overall yield returns to fertilizer is obtained via a 1% yearly reduction in fertilizer applications, the plantation saw an average of $4.84 per hectare yearly savings in fertilizer spending throughout the life of the palm, resulting from a removal of an average of 8.64 kg of fertilizer per hectare per year. Per hectare NPV increased by $39.67, representing a 4.68% increase in NPV for the plantation given the plantation's current application levels. When the percent increase in overall yield returns to fertilizer is obtained by an equivalent one percent yearly increase in yield, benefits per year increased on average by $19.34 per hectare from an increased average production of 0.17 kg/ha FFB, though average per hectare harvesting costs also increase by $3.70. Per hectare NPV increased by $122.44, or 14.46% (Table 2.5).

Breakeven analysis of yield loss associated with the changes in fertilizer management revealed that a yield loss of 0.32% would reduce the net benefit of the 1% decrease in fertilizer use to zero. When overall spending on fertilizer remains constant but is instead reallocated across areas of the plantation or across nutrients, the management change would generate no net change in benefits if overall yield change was 0% and would need to generate a net yield loss in order to decrease the plantation's net returns.

2.5 Discussion

The results from the spreadsheet model suggest that even moderately successful efforts to improve yield returns to fertilizer can lead to important improvements in the plantation's economic performance, with a one percent improvement in the yield/fertilizer ratio leading to a 4.68% and 14.46% increase in the plantations NPV given the plantation's current levels of fertilizer application, depending on whether the improvement in yield returns to fertilizer came from decreasing applications of excess fertilizer or from increasing the return in terms of yield from current levels of fertilizer use. Given that fertilizer spending alone was responsible for 29.5% of discounted total costs, including initial capital costs of stand establishment, it is not surprising that marginal improvements in the use efficiency of this resource would generate large impacts on overall measures of financial performance. For existing plantations in the Llanos, targeting yield returns to fertilizer may thus be a promising strategy to improve overall returns from palm oil production given a budget constraint on fertilizer spending (Corley, 1977; Fedepalma, 2016).

The financial response to marginal changes in yield returns to fertilizer are dependent on the relative prices of fertilizer and FFB's (Corley and Tinker, 2016). At the current prices of $0.60 per kg of compound 13-5-27-5 fertilizer and $0.12 per kg of FFB, the price ratio of fertilizer to FFB is 5, in line with average values for the Llanos (Fedepalma, 2016). However, this ratio is subject to significant temporal variability, as seen from the high standard deviation on per hectare NPV of $407.02 (Table 2.4) (Espinoza and Garcia, 2008; Fedepalma, 2016). Colombia must import nearly all of its mineral fertilizer, and as a minor market must act as a price taker (Espinosa and Garcia, 2008; Word Bank, 2012). The largest single use for Colombian palm oil, on the other hand, is for generating biodiesel to satisfy government mandates for automotive fuel blending, and the price of Colombian oil palm is thus largely determined as a response to national energy policy (Rozo and Romero, 2012). Insofar as factors such as domestic policy decisions can have large effects on oil palm prices for domestic producers without affecting fertilizer prices, the effects on plantation financial performance from changes in yield returns to fertilizer can vary accordingly. However, given a twenty-five-year production cycle and the difficulty of matching short-term changes in fertilizer application with a corresponding yield response, potential investors seeking the evaluate estimated benefits and costs of palm oil production must respond to expected long term trends in input and output prices (Carter et al., 2007).

Whether it is possible to attain measurable improvements in yield returns to fertilizer in Llanos oil palm production is a more difficult question than estimating the resulting margin effects on plantation financial performance. However, the current practice of uniform fertilizer applications despite large variability in both soil properties and yield within the target plantation suggests that there is room for improving yield returns to fertilizer by better adjusting fertilizer applications according to expected variable yield returns, which could be estimated both from soil properties and from past yield levels (Foster, 2003). Furthermore, estimating marginal yield response to fertilizer applications involves an additional degree of uncertainty, and thus changing fertilizer management in the pursuit of improving yield returns to fertilizer involves an inherent degree of risk of generating unintended yield losses. As noted from the results of the breakeven analysis of yield loss associated with the changes in fertilizer management, the nature of this risk is different if one seeks to reduce excess fertilizer applications than in reallocating current resources within the plantation when fertilizer application is constrained by a budget constraint. Reducing fertilizer application involves an explicit prediction about both the quantity of expected yield losses and the relative value of fertilizer versus oil palm FFB, with only a 0.32% yield reduction being necessary to eliminate the savings of a 1% reduction in applied fertilizer at current prices. This result highlights the impact of a budget constraint on optimal fertilizer management, given variable marginal response application at different dosages. Faced with a budget constraint, reallocating resources within the plantation to areas/nutrients with higher marginal yield response while keeping overall spending constant separates the risk of changes in relative input and output prices from the change in management, since overall input spending is kept constant. Additionally, while the magnitude of the improvement in financial performance remains proportional to the magnitude of the difference in marginal yield response between the two areas/nutrients, a loss is only generated if the overall sign of the difference in marginal yield response is wrong, i.e. is fertilizer is moved from a place of higher marginal yield response to a place of lower marginal yield response. Faced with a budget constraint on fertilizer spending, reallocating resources for fertilizer within the plantation may thus involve a lower level of risk than reducing overall applications, especially if current application levels are not high enough that potential excess fertilizer is easily identified.

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CHAPTER 3. INTERGRATING RASTER-LAYER SOIL PROPERTY MAPS WITH THE PORIM MODEL TO CALCULATE YIELD RESPONSE TO FERTILIZER IN OIL PALM

3.1 Abstract

The PORIM model was developed by the Malaysian Palm Oil Board in order to help oil palm (*Elaeis guineensis* Jacq.) plantations achieve economically optimal fertilizer applications, and has become a standard used among plantations in Malaysia and Indonesia (Foster et al., 1985 a,b; Corley and Tinker, 2016;). The model is a statistically-based system that uses site characteristics of individual plantations as parameters in a series of equations that aim to predict yield levels at a given level of applied N and K fertilizer, including topographic and soil chemistry characteristics (Foster et al., 1985 a,b). Though typically run using low-resolution vector-layered data, the equation systems used by the PORIM model to describe the interactions between soil properties and oil palm yield response to fertilizer can also be made to accept high-resolution raster-layers as soil property inputs. As such, the PORIM model offers a potential for generating optimal fertilizer management strategies in oil palm plantation based on digital soil mapping techniques developed from recent advances in remote sensing technologies. This study used continuous 30x30m resolution digital soil property maps to quantify soil variability within a study site near Villanueva, Casanare in the Colombian Llanos. The digital soil maps used were based on topographic analysis using Digital Elevation Models (DEM's) in conjunction with georeferenced soil sampling. Additionally, Modified Catchment Area (MCA), an iterative measure of a landscape position based on a DEM representing a grid cell's propensity to lose or gain soil water, was used to model the yield-limiting effects of moisture stress based on study site-specific measurements of the correlation between soil moisture and oil palm yield. Based on these

parameters and average market data, constrained optimization programming was used to find the optimal allocation of N and K fertilizer within the plantation that would maximize the plantation's net revenues subject to incurring no additional fertilizer expenditures or operational costs related to fertilizer applications. As a result of improved allocation of fertilizer within the plantation, estimated yearly Fresh Fruit Bunch (FFB) production per kg of N+K fertilizer applied increased from a current 57.1 kg FFB to 64.8 FFB, resulting in an additional average net revenue of $236.61 per hectare per year. Since Colombia is a minor oil palm producer, the parameters used by the PORIM model have not been tested for the Llanos soils of this study site, and so the results of the model are subject to a degree of uncertainty. However, the digital soil mapping process based on the SRTM DEM is immediately applicable in Malaysia and Indonesia, where the PORIM model was been extensively tested, and where the majority of the world's palm oil is produced (Foster et al., 1985a, b; Corley and Tinker, 2016). The goal of this paper is to demonstrate a potential methodology for integrating high-resolution soil property rasters within the yield-response models used in the oil palm industry to calculate optimal fertilizer rates in plantations where the PORIM model is already commonly employed.

3.2 Introduction

Oil palm plantations in the Llanos region of Colombia face strong pressures to increase their understanding of infield variation within their holdings to improve yield return on fertilizer and other inputs (Fedepalma, 2016). Fertilizer prices in Colombia are often considerably higher than in neighboring countries, resulting from poor infrastructure spanning across geographically challenging terrain, limited domestic production, and market distortions in the import and distribution of fertilizers (Espinosa and García, 2008). Along with labor for harvesting, fertilizers represent plantations' largest variable expense, and the result is that rising fertilizer costs have squeezed the profit margin out of palm oil production in the country (Fedepalma, 2016). The effect has been particularly severe in the Llanos region of eastern Colombia, where added logistic expenses due to geographical isolation further exacerbate the problem of high input costs (De, 2012). In response, producers have sometimes been forced to indiscriminately reduce fertilizer applications across their holdings, possibly reducing yields and sacrificing long-term value. However, palms can display considerable variation in yield response to fertilizer even when climate, genetics and management are constant, due to variable soil conditions at the field-scale (Woittiez et al., 2017). Uniform applications across large planted areas are thus unlikely to achieve economically optimal returns to fertilizer applications (Webb, 2009). There is thus a particular need in the oil palm sector of the Llanos to implement methods for capturing soil variability, identifying factors relevant to local agronomic performance and yield response and developing variable-application strategies for optimizing economic returns to fertilizer application.

Potential oil palm yield is determined primarily by photosynthetically active radiation (PAR), temperature, ambient CO_2 concentration, and crop genetic characteristics under perfect crop management (van Ittersum and Rabbinge, 1997). However, PAR, temperature, ambient CO_2 concentration and genetic characteristics are generally uniform within an individual plantation, and so are not commonly the drivers of yield variability at the field scale (Fairhurst and Griffiths, 2014; Woittiez et al., 2017). At the scale of individual plantings, yield is primarily limited by soil water conditions and secondarily by nutrient availability (Tinker, 1984; Lee and Ong, 2006; Lobell et al., 2009). Water availability is considered the primary constraint in palm oil production in most plantations, with a linear relationship between plant-available water and yield (Corely, 1996; Palat et al., 2008; Carr, 2011). Oil palm requires large quantities of soil moisture, transpiring approximately 6 mm of water per day year-round under non-limiting conditions, but average actual transpiration rates are usually 4.0-6.5 mm day^{-1} in the rainy season and 1.0-2.5 mm day^{-1} during dry periods (Carr, 2011). Almost all of the world's oil palm is rainfed and is typically planted in regions of at least 2000 mm of annual rainfall (Corley and Tinker, 2016). However, though tolerant of temporary flooding, oil palm is also highly intolerant of persistent waterlogging (Lee and Ong, 2006). Severe reductions in yield have been observed in palms where waterlogging is a common problem, though the magnitude of these reductions has so far been poorly quantified (Lee and Ong, 2006; Carr, 2011; Abram et al., 2014). The mechanism by which waterlogging has been shown to reduce oil palm yield is the impaired respiration of submerged roots, which leads to sharp drops in water as well as nutrient uptake (Corley and Tinker, 2016), and has been associated with photosynthetic activity and transpiration rates that are three to four times less than in well-drained soils (Henson et al., 2008). Achieving high yields in oil palm that are not significantly limited by soil moisture conditions requires maintaining high levels of soil moisture year-round while avoiding waterlogging even under intense rainfall. The ability to maintain such optimal conditions is highly soil and site specific, and largely dependent on rainfall patterns, soil texture and topography (Paramananthan, 2000; Woittiez et al., 2017).

Nutrient uptake is highly dependent on adequate soil moisture and soil moisture uptake, and so under water-limiting conditions fertilizer applications often do not improve oil palm yields (Lee and Ong, 2006; Carr, 2011; Sun et al., 2011; Woittiez et al., 2017). However, under non-limiting soil moisture conditions, the availability of soil nutrients is commonly the most important limiting factor in achieving high yields in oil palm (Sun et al., 2011; Corley and Tinker, 2016; Woittiez et al., 2017). Oil palms are considered fairly normal in their composition and reaction to elements, with N, P, K, Mg, Ca and S as the major elements needed for vegetative growth and oil production, and Zn, Cu, Fe, B, Mo, Mn, Ni and Cl serving as trace elements present in plant tissues in low concentrations (Table 3.1) (Corley and Tinker, 2016). High yielding oil palms are particularly demanding of N and K, due largely to the high N and K content of fruit bunches, which typically range from 5 to 10 g/kg dry weight of N and 6 to 9 g/kg dry weight of K (Corley and Tinker, 2016). Oil palm is consistently responsive to N and K fertilizer applications, with continued response to applications as high as 250 kg of each N and K having been observed in many instances (Corley and Tinker, 2016; Ng, 1986; Sidhu et al., 2004; Vossen, 1970). Neither N nor K toxicity is known to occur in oil palm, and linear plus plateau as well as quadratic plus plateau response models have shown to closely fit data from field experimentations across a variety of sites (Vossen, 1970; Ng, 1986; Sidhu et al., 2004; Corley and Tinker, 2016; Woittiez et al., 2017). Response to P fertilizer has been observed in some settings, but is generally inconsistent, and yield plateaus between 25-50 kg P/ha. It is therefore common practice amongst plantations with high yielding stands to apply 25-50 kg/ha P to satisfy any maintenance requirements and avoid possible deficiencies (Vossen, 1970; Ng, 1986; Sidhu et al., 2001; Woittiez et al., 2017). Responses to applications of Mg and B have been recorded in some instances, but these are highly site-specific and applications of these nutrients are not common practice in most plantations (Foster and Chang, 1977; Foster, 2003).

Table 3.1 Mean nutrient concentration (g/kg of dry matter) in the tissues of mature oil palms (Ng et al., 1968).

Component	N	K	P
Leaflets	20.5	8.8	12.8
Rachis	3.7	14.9	0.7
Spear	13.3	17.0	1.4
Cabbage	28.6	40.6	5.5
Trunk	5.4	15.4	0.7
Roots	3.2	8.0	0.3
Whole palm	5.4	16.0	0.8

The simplest and oldest methods for calculating optimal fertilizer applications in oil palm were based on a nutrient balance approach, whereby total demands and sinks for a specific nutrient where estimated in order to calculate the added amount of fertilizer needed to sustain a target production level (Cooke, 1967; Ng and Thamboo, 1967). A nutrient balance was developed for K, which is a nutrient frequently impacting to palm oil production and has a simpler soil chemistry in most soils than N or P (Teoh and Chew, 1988; Henson, 1999c). However, accounting for storage and loss for each nutrient across multiple sinks has proven challenging, and the difficulty is compounded by the tendency of oil palm to store large amounts of nutrients across multiple years (Corley and Tinker, 2016). In order to provide plantations with a more easily implementable system for estimating yields at different levels of fertilizer application, the Palm Oil Research Institute of Malaysia (PORIM) [now the Malaysian Oil Palm Board (MPOB)] developed a statistically-based system, known as the PORIM system, that uses site characteristics of individual plantations as parameters in a series of equations that aim to predict yield levels at a given level of applied N and K fertilizer, including topographic and soil chemistry characteristics (Foster et al., 1985 a,b). The PORIM model assumes that P, Mg and minor elements are non-limiting, as is typically the case in most plantations (Foster et al., 1985 a,b ; Corley and Tinker, 2016). This model is thus intended to provide an estimate of annualized yield over the production cycle of mature oil palm at a given yearly application of N and K fertilizer (Corley and Tinker, 2016). The equations linking site specific variables to yield response were developed based on extensive trials across multiple years, with factorial trials in Southeast Asia, West Africa, and South America, with different equation sets developed for various soil series and climatic regimes (Foster et al., 1984b; Pacheco et al., 1985; Hartley, 1988). In this system, response curves to N under non-limiting K conditions and K under non-limiting N are individually calculated as quadratic equations with plateaus after reaching a critical point. Outputs from these functions are then used as inputs in a nested function that produces yield estimates at any level of N and K applied (Foster et al., 1985a,b; Corley and Tinker, 2016). The PORIM system has since become a widely used tool in the oil palm industry (Corley and Tinker, 2016).

This paper builds on methods for developing digital soil property maps of soil chemical, physical and hydrological properties in oil palm plantations using the FSM model at the 30x30m resolution of the Shuttle Radar Topography Mission Digital Elevation Model (SRTM DEM), (Owens and Ashtekar, 2013; Ashtekar et al., 2014; Martinez, 2018a). A primary goal of this paper was to develop a methodology for integrating high-resolution soil property rasters within the yield-response models used in the oil palm industry to calculate optimal fertilizer rates. Using continuous 30x30m digital soil property maps from a study site near Villanueva, Casanare, individual yield response curves for each grid cell were calculated from the soil property maps using the PORIM model. Additionally, in order to capture the effects of water stress on oil palm yield response to fertilizer, a new method was proposed for incorporating Modified Catchment Area (MCA) values derived from running terrain algorithms (TA’s) on an SRTM DEM into yield response estimates. The General Algebraic Modeling System (GAMS), a constrained optimization model, was used to find grid-cell specific optimal fertilizer applications that could determine economically optimal fertilizer rates under current market conditions and subject to the study site's plantation's current management constraints (Bussieck and Meeraus, 2004; Abdul et al., 2014). The PORIM model has not been tested in the Colombian Llanos, and no domestic equivalent has been developed, so its results for this test site are subject to an added degree of uncertainty. However, the digital soil mapping process based on the SRTM DEM is immediately replicable in Malaysia and Indonesia, where the PORIM model was been extensively tested, and where the majority of the world's palm oil is produced (Foster et al., 1985a, b; Corley and Tinker, 2016). This paper thus hopes to demonstrate how high-resolution soil property rasters can be integrated with the PORIM model, at a time when interest in raster-based precision-agriculture methods has grown considerably but has not yet become common in oil palm production.

3.3 Methods

3.3.1 Plantation Practices

The study site was a 5,220 hectare oil palm plantation in the Colombian Llanos, in the municipality of Villanueva, Casanare. The soils of the plantation were uniformly classified as Typic Fluveaquents, with slopes of 0-3%, from recent alluvial deposits from the Eastern Andes mountain range, with a depth greater than 100cm (IGAC, 2014). Yearly precipitation in the plantation regularly exceeded 2000mm, while average temperatures were about 27 °C (Table 3.2).

Table 3.2 Yearly precipitation and average temperature for 2010-2016 for the study site; a 5,220ha oil palm plantation in the department of Casanare in the Colombian Llanos

Year	Precipitation (mm)	Temperature (ºC)
2010	2866	27.0
2011	2195	26.7
2012	2535	26.8
2013	2265	27.0
2014	2116	26.6
2015	1957	27.0
2016	2003	27.2

Management practices and input applications were identical throughout the plantation and followed best practices as defined by the Colombian National Federation of Palm Oil Growers (Fedepalma, 2016). Palms received uniform applications of premixed 13-5-27-5 (N-P-K-Mg) fertilizer at the rate of 4 kg/palm from the onset of production, for a total yearly per hectare application of 83 kg/ha N, 32 kg/ha P, 173 kg/ha K, and 32 kg/ha Mg. The fertilizer was a physical mixture of urea, monoammonium-phosphate, muriate of potash, and magnesium oxide.

The plantation was comprised of six management zones of different size. Management zones were planted at the same time and from the same genetic material, with their exact size and shape determined by the borders of neighboring properties available for sale as the plantation expanded and new plantings were added starting in the 1970's. Since management zones are too large for a harvesting crew to harvest in a workday, they are divided into smaller harvesting units. There was no consistent methodology used by different plantation's managers to divide management zones into harvesting units as new management zones were added over time, thus they are highly irregular in shape. Fertilizer is manually applied by a contracted work crew to one harvesting unit at a time, twice-yearly during the wet season.

3.3.2 Constructing Grid-Cell Specific Yield Response Curves

The PORIM model uses seven site characteristics (X_1-X_7; Table 3.3) and a set of five nested equations to predict yield response to applied N and K in the soil class found in the study site (Foster et al., 1985a,b):

Table 3.3 Rainfall and soil characteristics used in the PORIM model to predict yield response to N and K fertilizers (Foster et al., 1985a,b).

Variable	Site Characteristics
X_1	Extractable K (cmol/kg)
X_2	Annual rainfall (mm/year)
X_3	Total extractable bases (cmol/kg)
X_4	Clay (%)
X_5	Silt (%)
X_6	Total extractable cations (cmol/kg)
X_7	Average rainfall (mm) during 3 months after fertilizer application

Yield in kg of FFB without K fertilizer at non-limiting N is calculated as:

1)

$$Y \text{ at } K_0N_{max} = 22.50 + 9.662X_1 + 0.002599X_2$$

Yield in kg of FFB without N fertilizer at non-limiting K is calculated as:

2)

$$Y \text{ at } N_0K_{max} = 22.44 + 0.004535X_2$$

Y at K_0N_{max} from Equation 1 is used in the following equation to calculate K response at non-limiting N:

3)

$$dY/dK = 1.836 – (0.01591X_6 – 0.007733X_5)*Y_{K0Nmax}$$
$$– 0.2356X_5 + 0.4095X_6 – 0.001566X_7$$

Y at N_0K_{max} from Equation 2 is used in the following equation to calculate N response at non-limiting K:

4)

$$dY/dN = 9.739 – (0.4630 + 0.014911X_4 – 0.0001409X_2)*Y_{N0Kmax}$$
$$– 0.01029X_4 + 0.1086*10^{-5} X_3^2$$

Continuous yield response curves for each N and K fertilizer were fitted by finding the parameters a, b and c which minimized the sum of squares of the residuals in the quadratic equation $Y=aX^2 + bX + c$, where Y is yield in tons of FFB and X is amount in kg of applied fertilizer N or K. Additionally, yield plateaus are established at 250 kg of each N and K, resulting in quadratic-plus-plateau response models for individual nutrient applications (Foster et al., 1985a,b; Corley and Tinker, 2016).

Yield at any combination of N and K fertilizers was found using $Y_{N.Kmax,}$ which is yield at a fixed amount of N fertilizer in kg at non-limiting K, and $Y_{K.Nmax}$, which is yield at a fixed amount of K fertilizer in kg at non-limiting N (Foster et al., 1985a,b):

5)

$$Y_{NK} = -22.71 + 1.10Y_{N.KMax} + 2.627\,Y_{K.Nmax} - 0.04656\,Y^2_{N.Kmax}$$

$$+ 0.0008651Y^2_{N.Kmax} * Y_{K.Nmax} - 0.06913Y^2_{K.Nmax} + 0.0007513\,Y_{N.KMax} * Y^2_{K.Nmax}$$

Equation 5 is bivariate function that is concave for all non-negative values of Y_{NK} (Figure. 3.1).

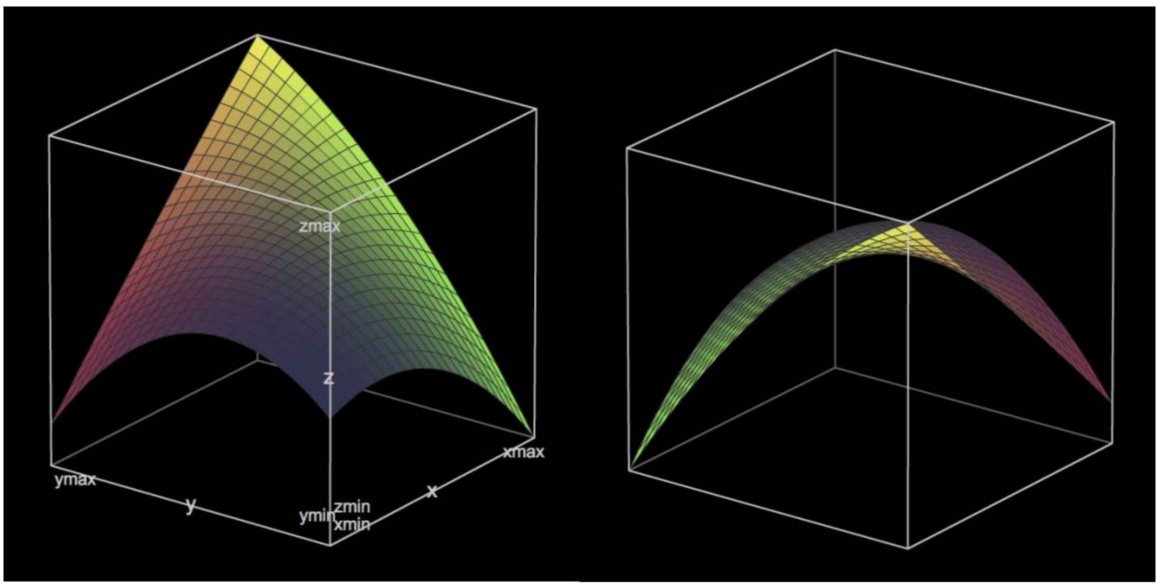

Figure 3.1 Bivariate function that outputs yield at any combination N and K (Equation 5) as seen for yields 0-50 tons FFB. X- and Y-axis are $Y_{N.Kmax}$ and $Y_{K.Nmax}$, respectively yield at a fixed amount of N fertilizer in kg at non-limiting K and yield at a fixed amount of K fertilizer in kg at non-limiting N.

3.3.3 Using Modified Catchment Area (MCA) to Modify Fertilizer Yield-Response Curves According to Soil Moisture

Modified Catchment Area values were used to adjust predicted yield increments using the PORIM model according to the following formula:

6)

$$Y_{MCA} = A^* F(N,K)$$

where F(N,K) is the output of Equation 5 and A is a scalar value $0<A\leq 1$. For locations within Management Zones where increasing MCA values were negatively correlated with yield, indicating excessive moisture, the scalar value A was determined as:

$$A = 1-\beta_1^* [MCA_{min} - MCA] \tag{7}$$

where β_1 (-0.0152) is the negative linear correlation coefficient between MCA and percent yield loss observed in the plantation due to soil moisture excess (Martinez, 2018a), MCA_{min} is the grid cell with the lowest MCA value within that Management Zone and MCA is the MCA value of the current grid cell. For locations within Management Zones where MCA values were positively correlated with yield, the scalar value A was determined as:

$$A = 1-\beta_2^* [MCA_{max} - MCA] \tag{8}$$

Where β_2 (0.0083) is the positive linear correlation coefficient between MCA and associated percent yield loss observed in the plantation due to soil moisture deficit (Martinez, 2018a), and MCA_{max} is the grid cell with the highest MCA value within that Management Zone.

3.3.4 Optimization Modeling of Fertilizer Applications using the General Algebraic Modeling System (GAMS).

With yield-response curves in place for each grid-cell, the decision of how much fertilizer to apply in each location was conceived as a profit-maximization problem and solved using the General Algebraic Modeling System (GAMS). GAMS is a high-level level modeling system for mathematical optimization, designed for linear, non-linear and mixed-integer optimization problems (Bussieck and Meeraus, 2004). The optimal fertilizer application on the plantation was calculated as a Lagrange function $\mathscr{L}$ such that:

$$\text{Max } \mathscr{L} = [P_{FFB} * Y - P_N * N - P_K * K] - \lambda_1[A*F(N,K) - Y] - \lambda_2[c - P_N * N - P_K * K]$$

Where:

1) P_{FFB} is the price of palm FFB's in $/kg.

2) Y is a vector of yield values for each grid cell in kg/ha.

3) P_N and P_K are respectively the price of nitrogen and potassium fertilizer in $/kg.

4) N and K are respectively vectors of amounts of fertilizer N and K applied in kg/ha.

5) A*F(N,K) is the scaled function that produces yield estimates from fertilizer dosages.

6) c is the budget constraint on fertilizer spending in $.

7) λ_1 is the shadow price of changes in yield response to fertilizer applications.

8) λ_1 is the shadow price of changes to the budget constraint on fertilizer spending.

Additionally, several constraints were imposed on the problem to reflect the plantation's management constraints:

1) Since the plantation's fertilizer is pre-mixed prior to delivery, a single N/K ratio was used.
2) Since fertilizer is manually applied and precision-application within harvesting units is impractical, each grid-cell in a harvesting unit received the same dosage of fertilizer.

Additionally, non-negativity constraints were imposed for fertilized applications and FFB yield. A value of \$0.12/kg was used for P_{FFB}, and \$0.75/kg was used for each P_N and P_K (Montoya et al., 2014). With these prices and at the current application rates of 83 kg/ha N and 173 kg/ha K, the plantation's annual budget for N and K fertilizers was \$346,176, or \$192 per hectare.

3.4 Results

3.4.1 Fertilizer Reallocation and Predicted Yield Increases

The results from the PORIM model suggest that total estimated annualized yield for the plantation following the optimized fertilizations strategy could reach 29,897 tons FFB, compared to the current actual yield of 26,342 tons FFB. This reflects a hypothetical 13.5% increase in yield, reflecting the production of 3,555 additional tons of FFB per year from the 1,803 ha in production. This increased estimated production represents a change from 14.610 tons/ha/yr to 16.582 tons/ha/yr. At the assumed price of \$0.12/kg FFB, the yield increase represents a \$426,600 increase in yearly revenue for the plantation, or \$236.61 increased revenue per hectare.

Recommended total fertilizer application according to the model was 143,245 kg N and 318,323 kg K, compared to the currently applied amount of 149,649 kg N and 311,919 kg K.

This represents a modest change in the N/K ratio from 0.48 to 0.45, in favor of slightly higher K applications. Per the model's constraints, the new N/K ratio in the applied fertilizer was the same throughout the plantation. Recommended combined N and K fertilizer application rates differed considerably from the current uniform rate of 256 kg/ha/yr, ranging from a 39% decrease (156 kg/ha/yr N+K) to a 47.5% increase (377.6 kg/ha/yr N+K) from current application levels (Figure 3.2).

The potential yield changes estimated by the PORIM model also varied considerably from their current actual levels, ranging from a decrease of as much as 40.5% to an increase of as much as 208.4%, with an average 13.5% increase (Figure 3.2). Of this increase, 0.06% was attributable to the change in N/K ratio from 0.48 to 0.45, while the remaining 99.94% was attributable to the overall redistribution of N+K fertilizer to areas of higher predicted marginal response to fertilizer application. Of the yield increase attributable to N+K fertilizer redistribution, 22.4% percent was attributable to reallocating fertilizer according to MCA, while the remaining 77.5% was due to variability in the soil physical and chemical characteristics originally included in the PORIM model: extractable K, total extractable cations, and soil texture.

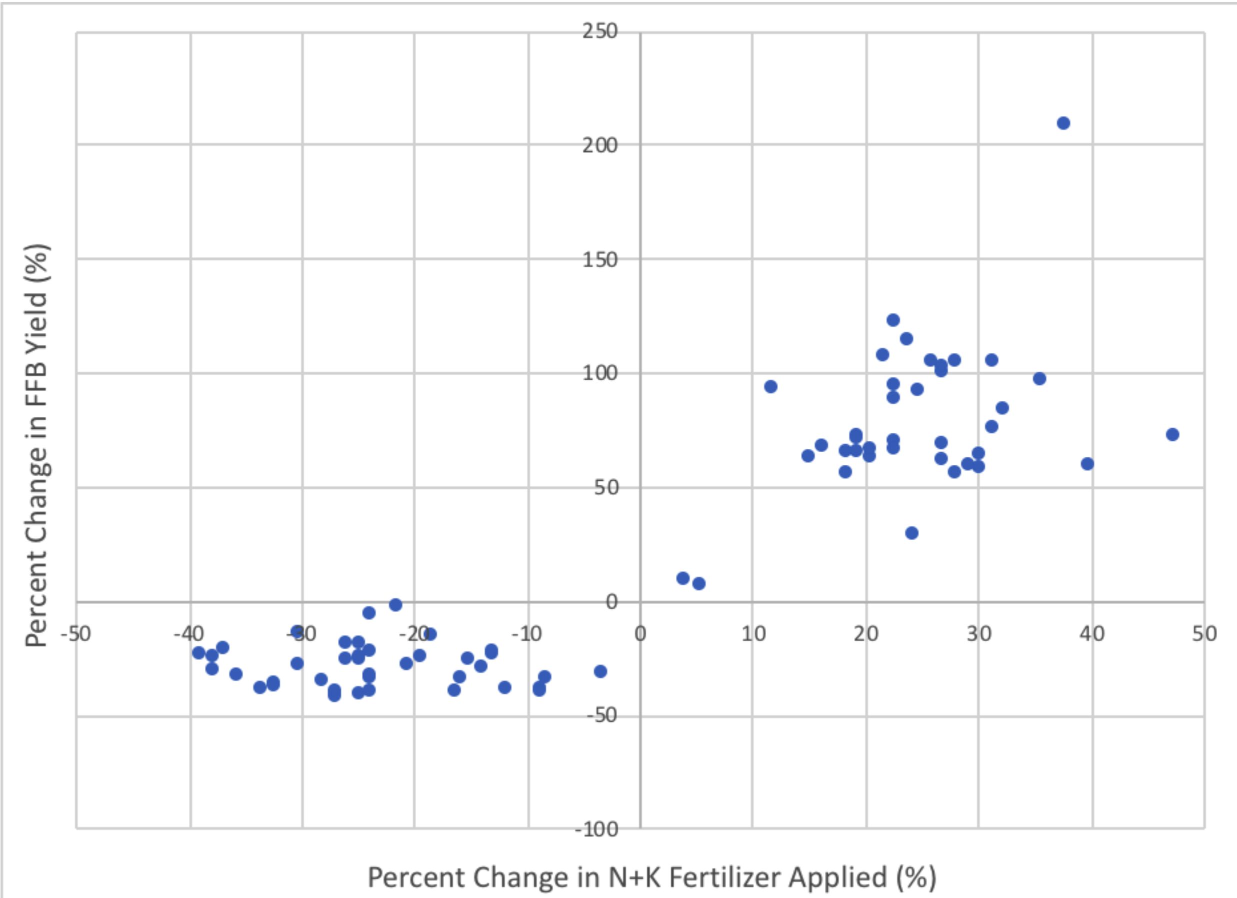

Figure 3.2 Scatterplot of percent change in recommended application of total N and K fertilizer resulting from optimization analysis using the PORIM model of yield response to fertilizer applications in oil palm and raster-layer soil property maps derived from the SRTM DEM and geo-referenced soil sampling, together with the estimated change in yield. Each point represents 1.25% of the plantation's 5,220 hectares. Recommended percent fertilizer change based on current uniform applications of 256 kg/ha of total N and K fertilizer (83kg/ha of N and 173 kg/ha of K).

Including MCA in the model lowered the estimated potential productivity of 48.7% of the area of the plantation, with an average reduction in yield potential of 25.7% for affected areas and 12.6% for the entire plantation. Individually, moisture deficiency overall lowered plantation yield potential by 3.6%, while moisture excess caused a 9.0% overall decrease in yield potential.

3.4.2 Results of Marginal Analysis of Fertilizer Expenditure

Overall predicted return in kg of FFB per each kg of N applied using the PORIM model increased from 176 kg FFB to 208 kg FFB, while overall return in kg of FFB per each kg of K applied increased from 85 kg FFB to 94 kg FFB. Overall return in kg of FFB per each kg of combined N and K fertilizer applied increased from 57 kg FFB to 65 kg FFB. The budget constraint on the optimization model was binding, with an associated Lagrange multiplier of $1.66 of revenue per an additional dollar spent on fertilizer. This indicates that increasing expenditure on fertilizer would be profitable for the plantation, and that consideration of soils, water and landscape can improve profits if considered in the fertilizer application.

3.5 Discussion

The results of this study demonstrate how digital soil mapping can be incorporated with the PORIM model to generate precision fertilizer management strategies and model the expected change in yield. The constraints imposed on the fertilizer application optimization problem reflect the scope of decision-making options that are available to plantation managers without incurring additional costs, be it by 1) raising their budget for fertilizers, 2) incurring the logistical and retail costs of handling multiple fertilizer grades, or 3) changing or imposing additional demands on their contracted work crews for applying fertilizer. The increased revenue of $426,600 ($236.61/ha) thus represents the hypothetical net gain for the plantation. Two different pathways were identified to increase the plantation's overall yield by better allocating current resources without incurring additional costs. The first pathway involves the tradeoff in the marginal yield response between N and K in the plantation's fertilizer blend. The PORIM model assumes both substitution and complementarity between N and K in palm oil production, with a concave production function with convex isoquants that indicate diminishing returns to each element alone or to two elements in fixed combinations (Heady et al., 1955; Foster et al., 1985a,b). This suggests both that even if at a physiological level N and K serve different functions and are ultimately not substitutable, marginal applications of each nutrient on its own will produce a yield response, and thus that the two elements can replace each other at a diminishing rate in producing a given yield (Heady et al., 1955). The economic optimal N/K ratio occurs when the marginal yield response to additional applications of each nutrient are equal, which at the given prices of $0.75/kg for each N and K occurred at an N/K ratio of 0.45. This is in line with Fedepalma's recommendations (Munévar, 2001), and very close to the plantation's current ratio of 0.48, and the small space for improvement explains why improving the N/K ratio only accounted for 0.06% of the yield increase estimated by the model.

The second pathway for increasing the plantation's overall yield without increasing operational costs or spending on fertilizers was reallocating fertilizer from areas of lower marginal response to areas of higher marginal response. The optimal allocation of fertilizer occurs when the marginal yield response to fertilizer is equal throughout the plantation (Heady et al., 1955). The diminishing marginal returns associated with oil palm response to N and K imply that while marginal yield responses to fertilizer application within the plantation remain unequal, then greater yield can always be obtained from the same amount of fertilizer by reallocating from areas of lower marginal yield response to areas with higher marginal yield response (Heady et al., 1955). Given the existence of significant variability in terms of soil chemical, physical and hydraulic properties (Martinez, 2018a), and the importance of these soil properties in determining oil palm yield response to fertilizer (Corley and Tinker, 2016), one would expect that the plantation's current practice of uniform applications would result in highly unequal rates of marginal yield response. Reallocating overall N and K fertilizer within the plantation thus accounted for 99.94% of the 13.5% increase in overall yield predicted by the model. Given that there were no additional costs associated with running the model and implementing its recommendations, the shadow price of a unit change in yield in kg/ha of FFB was equal to the current price of FFB of \$0.12/kg. Given an equal price of \$0.75 per kg of N and K fertilizer used in the model, the marginal effect on total fertilizer cost of a change in the N/K ratio was \$0 (Table 3.4).

Table 3.4 Shadow prices of a) changes in yield, b) the budget constraint on fertilizer spending, and c) changes in the N/K ratio on plantation profits on a per hectare basis.

a)	Unit change in yield (FFB kg/ha)	\$0.12
b)	Releasing budget constraint by a dollar	\$1.60
c)	Unit change in N/K ratio on fertilizer cost	\$0

The PORIM model for the soils of the plantation (Typic Fluveaquents) assumes that field variability in yield response is primarily based on extractable K, total extractable bases, clay and silt content (Foster et al., 1985a,b). Extractable K and total extractable bases varied significantly within the plantation (mean K = 0.30 ± 0.19 meq/100g, total extractable bases = 4.2 ± 2.2 meq/100g), while clay and silt showed less but still significant variability (mean clay = 31 ± 5%, silt = 27 ± 2%), so it would be expected that the PORIM model would predict differing yield response rates at different locations, in this case accounting for 77.5% of the estimated increase in yield from improving fertilizer allocation. However, given the statistical nature of the PORIM model, it is very difficult to elucidate the precise agronomic relationship underlying the estimated differences in yield response rates, or even why these four specific soil characteristics were included in the model (Corley and Tinker, 2016). It is also worth noting that, while the equations in the PORIM model are based on numerous trials across different sites (Foster et al., 1984b; Pacheco et al., 1985; Hartley, 1988), they nevertheless constitute a generalization that may deviate considerably from actual fertilizer responses at the study site. Field trials measuring yield response to N and K fertilizer application conducted at the study site may provide a means to adjust the PORIM equations to the plantation and improve the accuracy of the model's yield response estimates.

Including the MCA values as a means to capture the yield-limiting effects of soil moisture stress on oil palm yield response to fertilizer was a new element in the implementation of the PORIM model for this study site. Given the high correlation between MCA and yield seen in the study cite (Martinez, 2018a), including MCA in the model using the correlation coefficients seen in the study site served as a means of incorporating a key site-specific variable into the generalized PORIM model. Following previous studies of the effect of both excessive and insufficient moisture on oil palm growth as a linear relationship, MCA-related moisture stress was presented as a scalar variable capable of limiting overall palm yield at the affected location. As a result overall estimated yield in the plantation was depressed 12.6%, and of the yield increases estimated by the model, 22.4% were attributable to redistributing fertilizer according to yield response variability associated with yield limitations related to soil moisture.

Currently, the plantation produces 57.1 kg FFB for every kg of combined N and K fertilizer applied. At prices of $0.75/kg of both N and K and an FFB price of $0.12/kg FFB, this represents an average return of $8.57 for every dollar spent on fertilizer. The model's estimate is that with better allocation of its current resources, the plantation could produce 64.8 kg FFB for the same kg of combined N and K fertilizer, resulting in a $9.72 return on the dollar. However, the diminishing returns inherent in oil palm response to fertilizer result in a lower marginal return than the plantation's average return on fertilizer spending, and the Lagrange multiplier associated with the model's budget constraint indicates that at the current spending of $192 per hectare of N+K fertilizer, the marginal return to a $1 increase in N+K fertilizer spending would be $1.66. However, this represents only an expected marginal return at current prices, and so is susceptible to significant risk and short-term fluctuation. Nonetheless, understanding the marginal return on fertilizer spending is crucial for oil palm companies, since fertilizer spending is the variable cost that is most often adjusted to accommodate short-term changes in the company's finances or market expectations (Montoya et al., 2014).

In this particular study site, results arising from the PORIM model are subject to a high degree of uncertainty given that the PORIM model was developed for Malaysia and has not been tested in Colombia. The extensive field testing needed to develop and test the PORIM model is time consuming and expensive, due in large part to the particular difficulties of evaluating yield response to fertilizer in oil palm (Corley and Tinker, 2016). No equivalent model to directly link soil properties to yield response curves yet exists for the Llanos or any region of Colombia, though the national research institute for oil palm, Fedepalma, has expressed interest in developing precision agriculture methods for Colombian oil palm (Lizarazo, 2013). However, the methods demonstrated in this paper are immediately replicable in Malaysia, where the PORIM model has been extensively tested. It is the hope of the author that this paper can demonstrate a potential methodology for integrating high-resolution soil property rasters within the yield-response models used in the oil palm industry to calculate optimal fertilizer rates in plantations where the PORIM model is already commonly employed.

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CHAPTER 4. CONCLUSIONS AND RECOMMENDATIONS

The primary conclusion from this study was that topography has a significant effect on oil palm yield in the study site and was a driver of wide variability in yield response to fertilizer. In particular, the results from this study suggest that soil moisture was a primary determinant in oil palm productivity and should be taken into account in formulating fertilizer management strategies for oil palm plantations. The conclusion that the Modified Catchment Area algorithm (MCA) run on a 30m SRTM DEM consistently and accurately captured topography-driven variability in soil moisture across the study site was particularly noteworthy, given that the SRTM Digital Elevation Model (DEM) is freely available worldwide and the necessary GIS software to run the MCA algorithm is also broadly available. This suggests that MCA and global DEM's could be a useful and cost-efficient tool for plantation managers trying to understand yield variability across plantations and generate better fertilizer management plans. Given the similarity in environmental conditions and management practices across oil palm plantations in the Llanos, it is possible that topography might play a similar role across other plantations in the region, and perhaps even amongst plantations the major oil palm producing regions of Malaysia and Indonesia. It would therefore be recommended that the procedures for generating MCA maps and comparing them to plantation yields be replicated in other sites in order to evaluate the applicability of these methods to other oil palm plantations, both in the Llanos and in other oil palm producing regions. Such efforts could potentially result in a better understanding of how soil moisture affects oil palm yield and response to fertilizer and produce more robust backing for incorporating DEM-based digital methods for incorporating topography-based analyses of soil moisture into the formulation of oil palm fertilizer management strategies.

The development of digital methods for analyzing oil palm yield and management data as raster layers confirming to a high-resolution digital elevation model could also serve as a useful guideline to managers attempting to improve the economic returns they receive from spending on fertilizer, particularly under a budget constraint. The initial formulation of a formal optimization model for fertilizer applications could serve as an analytical basis for connecting agronomic insights on oil palm response to fertilizer applications and the logistic and economic parameters faced by plantations. The underlying yield response models in any economic optimization model should be continuously updated as our agronomic understanding of oil palm response to fertilizer under different conditions improves.

APPENDIX

A.1 Use of Remote Topographic Analysis in Digital Soil Mapping

Digital Elevation Model's (DEMs) are a representation of the Earth's surface and are used to provide a model of changes in elevation along terrain (Li et al., 2005; Hirt, 2016). Digital elevation models are often separated into two distinct types: digital terrain models (DTMs), which represent the bare ground without any objects such as plants and buildings, and digital surface models (DSMs) which include objects on the surface in their representations (Li et al., 2005; Hirt, 2016). Remote sensing technologies have made it possible to generate DEMs either via aircraft or from satellites, without the need from on-the-ground surveys. Two globally available DEM's made from satellite-based platforms are the Shuttle Radar Topography Mission (SRTM) 30m Global DEM and the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) 30m Global DEM. The SRTM Global DEM was constructed using images from synthetic aperture radar (SAR). Radar images taken in slightly different directions were used to construct a three-dimensional model of the Earth's surface (Burgmann et al, 2000). This technique, called Interferometric Synthetic Aperture Radar (InSAR, is based on theoretical research on cross-orbit interferometry developed in the late 80's (Gabriel and Goldstein, 1988). A Global DEM constructed using InSAR images is available from the Shuttle Radar Topography Mission, which carried a Spaceborne Imaging Radar-C/X-band Synthetic Aperture Radar (SIR-C/X-SAR) onboard the NASA Space Shuttle Endeavour on 11–22 February 2000 (Gabriel and Goldstein, 1988; Werner, 2001) The SRTM successfully collected data over 80% of the Earth's land surface, for most of the area between 60 degrees North and 56 degrees South latitude in 30 meter resolution (Burgmann et al., 2000). More recently, in 2009, another Global DEM has also been made available from ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer), a Japanese sensor mounted onboard the Terra satellite launched by NASA in 1999. The ASTER GDEM was constructed via the use of stereoscopic images to develop a three-dimensional image (Nikolakopoulos et al., 2006). Though several algorithms have been developed to accomplish this, they commonly rely on maximum correlation matching between pixels in paired image. ASTER provides high-resolution images in fourteen different bands of the electromagnetic spectrum, ranging from visible to thermal infrared light at a spatial resolution 15 and 90 meters (Zhen et al., 2001; Hirano, 2003). The Global Digital Elevation Map released to the public was created using stereoscopic correlation techniques with images taken from the VNIR part of the spectrum. The GDEM covers the planet from 83 degrees north to 83 degrees south, covering 99% of the planet's surface (Arabelos, 2000; Zhen et al., 2001; Hirano, 2003).

A.2 Modeling Soil Property Distributions using Functional Soil Mapping

The conceptual framework behind Functional Soil Mapping (FSM) is based on the model of soil formation described by Hans Jenny, whereby soil formation is a function of five soil forming factors: parent material, topography, climate, organisms (including human management) and time (Jenny, 1941). To the extent that the other four soil forming factors are held constant, topography will be the predominant driver of soil variability- a *ceteris paribus* condition that is most easily met at the field scale (Ashtekar and Owens, 2013; Ashtekar et al., 2014). Parent material was found to be uniform throughout the study site, as was management, original vegetative cover, and age of deposition of parent material (IGAC, 2014). Topography within the plantation was variable, with distinct undulations creating relative high and low points throughout the terrain. In this model, terrain algorithms derived from a DEM are used to describe and quantify topography's impact on soil property distribution and generate soil similarity vectors, and these in turn to generate continuous soil property maps from georeferenced soil analyses from standard laboratory methods. Traditional methods of assessing soil fertility and likely crop response to fertilizer applications have in large part depended on chemical analysis of soil samples (Bray and Kurtz, 1945; Peck et al., 1957; Jackson, 1958). While these can provide essential information about soil chemistry at individual points, they cannot on their own provide continuous information of how soil properties might behave across a terrain. Distribution of individual soil properties across a terrain are modeled according to the principle that grid cells with soil forming factors, as driven by topographic variation, will come to possess similar soil properties (Ashtekar et al., 2014). In the case of Colombian palm plantations, where the cost of intensive sampling and analysis for a large plantation might be prohibitive, soil analyses on their own can provide only snapshots with large blank spaces in between, and with no clear means to evaluate the representativeness of each sample (Sadeghian, 2010). New capabilities in remote sensing, on the other hand, can allow for continuous mapping of terrain properties (Li et al., 2005; Hirt, 2016). Lidar, shutter-aperture radar, and spectrophotometry can each be used to generate digital elevation models of a target area, and with the global SRTM and ASTER DEM's these are now available at no cost for most of the world's surface (Gabriel and Goldstein, 1988; Werner, 2001). However, remote sensing cannot directly measure soil chemistry in the manner in which a soil analysis can. In understanding how to combine terrain analysis from topographic models with geo-referenced soil chemical data, our understanding of soil fertility across a target area can surpass that attainable by either laboratory or remote sensing methods alone. The relationship between topography and soil chemistry has been studied for a long time, but it is only recently that remote sensing and GIS techniques have advanced sufficiently to be employed in describing terrain at the field scale (Milne, 1936; US Department of Agriculture Conservation Service, 1972; Gardner, 1998). This study seeks to apply the principles of this method directly in the context of effectively sampling and mapping a large plantation currently under production and with a controlled management plan, and developing a detailed understanding of topographic, chemical and physical variations in soils across the plantation under current management practices, with the purpose of understanding the effect of this variability on variation in yield response under uniform management and uniform fertilizer applications. In doing so, this study seeks to demonstrate how soil chemistry and remote sensing data can be successfully integrated to reveal a deeper understanding of agricultural production in the context of an individual oil palm plantation than could have been achieved by laboratory testing or remote sensing methods alone.

A.3 Yield Components of Palm Oil Production

Several factors can be important in determining oil palm yields, and considerable yield variability has consistently been observed both across and within individual plantings (Woittiez et al., 2017). Yield analysis of oil palm is predicated on understanding the particular physiological and ecological characteristics of this cropping system, which as a monocotyledonous perennial crop can be significantly different from other important oilseeds like soybeans and rapeseed (Woittiez et al., 2017). Oil palm has a typical life-cycle of twenty-five years, with plantings transplanted from a nursery reaching maturity in approximately twenty-five months and realizing peak yield four to six years afterwards (Heriansyah and Tan, 2005). Harvesting of mature stands is done manually approximately every 15 days for the duration of palm’s productive life cycle (Corley and Tinker, 2016). The harvested portion of the oil palm is an inflorescence comprising 1500-2000 fruitlets; these inflorescences are known as

Fresh Fruit Bunches (FFB's), and under ideal conditions can weigh 20-30kg and contain 20-25% palm oil under ideal conditions (Corley and Tinker, 2016). Palm oil yield can thus be separated into three distinct yield components: the number of FFB's, the weight per FFB, and the oil extraction rate (Corley, 1977). These separate components come together to determine overall oil palm yield and are in turn determined by complex interactions between oil palm physiology and ecology. Average yields for mature oil palm in Colombia's Llanos are approximately 3.9 t/ha/year of palm oil, though yields as high as 5-6 t/ha/year have been recorded, corresponding to >40 t/ha/year of FFB production (Munevar, 2001). As an unbranched monocotyledon, oil palm possesses a single shoot apical meristem, which is responsible for the initiation of the entire above-ground structure of the plant (Jouannic et al., 2011). Under favorable conditions, the meristem will remain continuously active during the life of the palm, and in mature palms will produce a new leaf- also called a frond- in a spiral phyllotaxy every fifteen days (Corley and Gray, 1976). Critically for oil palm yield analysis, fruit formation is driven by frond formation from the apical meristem. Inflorescences in oil palm are initiated in the axil of each new frond, with only a single inflorescence initiated per frond (Corley and Gray, 1976). The number of inflorescences available for future fruit development is thus directly dependent on the rate of leaf production, which is largely determined by planting material but is highly susceptible to environmental and edaphic conditions (Woittiez et al., 2017). Additionally, the number of possible inflorescences available for future fruit development is also dependent on the sex ratio between inflorescences. The sex ratio is dependent both on sex determination, which occurs in the initial weeks subsequent to initial frond formation, and on preferential abortion of female inflorescences (Woittiez et al., 2017). Both sex determination and preferential abortion are highly influenced by environmental stress, with a higher proportion of male inflorescences associated with stressful conditions. Both climatic stressors and nutritional deficiencies have been associated with a higher ratio of male inflorescences, which may potentially serve as a mechanism for palms to reduce the metabolic burden of fruit formation under suboptimal conditions (Woittiez et al., 2017). Climatic stressors, including nutritional deficiencies and hydrological deficit and excess, can impact yield by decreasing the number of female inflorescences and thus ultimately reducing the number of FFB's developed. Likewise, FFB weight and oil content have strong genetic components with experimentally known ceilings that vary by cultivar but are strongly dependent on climatic and edaphic conditions to realize their genetic potential (Corley and Tinker, 2016). Fertilizer use has been consistently found to affect both FFB weight and oil content (Ochs and Ollagnier, 1977), and have been found to be both positively and negatively correlated with rainfall in different sites, suggesting there can be soil moisture optima with yields decreasing in either direction (Sun et al., 2011). Yield components of oil palm are therefore rooted in the particular physiology of the crop but are dependent on suitable conditions to express the potential of the genetic material.

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