INVESTIGATING THE EFFECTIVENESS OF DIFFERENT PRECISION SOIL SAMPLING STRATEGIES FOR SITE-SPECIFIC NUTRIENT MANAGEMENT IN THE SOUTHEASTERN US

by

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ABSTRACT

Soil sampling is an important component of site-specific nutrient management in precision agriculture. To investigate how some of the commonly used precision soil sampling strategies influence the depiction of spatial nutrient variability and site-specific nutrient application requirements within agricultural fields, studies were conducted across multiple sites in 2022 and 2023. In the first study, soil sampling was conducted using grid sizes of 0.4, 1.0, 2.0, 3.0, and 4.0 ha in each field whereas the second study utilized management zones delineated using different spatial data layers for precision soil sampling. The nutrient application accuracy decreased with the increase in grid size; however, the total application costs were comparable among the grid sizes. For soil sampling based on management zones, soil sampling results were similar to the 0.4-ha grid sampling for some nutrients but were inconsistent across the nutrients (Lime, P, and K) and the fields used in this study.

INDEX WORDS: Grid Sampling, Zone Sampling, Site-Specific Nutrient Management, Variable-Rate Application,

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B.S., UNIVERSITY OF GEORGIA, 2020

A Thesis Submitted to the Graduate Faculty of The University of Georgia in Partial

Fulfillment of the Requirements for the Degree

MASTER OF SCIENCE

ATHENS, GEORGIA

2024

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August 2024

DEDICATION

For my mother (Laura Beth Tucker), who always pushed me to strive for excellence. Your unwavering love and support did not go unnoticed. I know you would have read this entire paper from cover to cover because you would be so proud. We will celebrate when we meet again.

ACKNOWLEDGEMENTS

Thank you to the Georgia Cotton Commission, Georgia Peanut Commission, and Georgia Farm Bureau for the financial support to conduct this research. Thank you to Dr. Simerjeet Virk for the advisement during my master's program. I have enjoyed getting to work alongside you and learning many different aspects of precision agriculture. I would also like to thank my committee members: Dr. Glendon Harris, Dr. Jason Lessl, and Dr. Matthew Levi for their expertise and guidance. To my fellow graduate students, Madan Sapkota, Ravi Meena, Amrit Pokhrel, Michael Goodnight, Coleman Byers, and all student workers, thank you for your help with the long field days of data collection. Finally, I would like to thank Lasseter Tractor Co. for allowing me an opportunity to take what I have learned from my educational career and apply it in a real-world setting.

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CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

1.1 Introduction

Most agricultural production fields in the southeastern United States have a large amount of spatial variability regarding soil physical properties and nutrient levels due to variations in climate, landscape, and crop management practices in the past. This within-field spatial variability oftentimes leads to crop variability which can be observed in stand development, crop health, maturity, and ultimately yield. While both soil and crop variability make crop management challenging; one of the main principles of precision agriculture is to accurately detect and address this variability using various precision practices and technologies. Precision agriculture techniques allow fields to be divided into relatively smaller areas of similar field or crop characteristics that can be managed separately from the adjacent areas. Variable-rate (VR) application of soil amendments and nutrients has proven to be cost-effective and increases yield to the area's potential when conducted appropriately. In fact, VR application to inform site-specific crop input management is one of the main components of precision agriculture as VR technology enables the right place and the right rate of the 4Rs of nutrient management (Johnston & Bruulsema, 2014). The 4Rs of nutrient management refer to the right rate at the right place, using the right source, and at the right time. With advancements in sensing and application technologies over the years, new and improved methods of site-specific crop management have been developed and adopted by the industry and growers.

Site-specific nutrient management requires proper soil testing to determine soil nutrient levels in a field. Different soil sampling approaches have evolved over recent decades from collecting a single composite sample from each field to a few samples based on the grower's knowledge or management history to precision soil sampling techniques such as collecting samples from certain size grids and pre-defined zones within a field. Before the adoption of any precision soil sampling methods, composite soil sampling to determine soil nutrient levels within the fields was a common practice (Mahler & Tindall, 1994). Composite soil sampling consists of collecting multiple soil cores from randomly selected locations across the field or sections of similar productivity or soil type based on historical knowledge of the field and then combining them to create a single or few samples for each field. The soil testing results from composite samples are used to apply lime or fertilizer at a single rate uniformly across the whole field. While the composite soil sampling and single-rate fertilizer application approaches are easier to implement, they usually result in relatively large areas of under- and over-application of fertilizer within the fields, thus causing more nutrient variability issues (Sawyer, 1994). Due to such issues associated with traditional composite sampling methods, grid- and zone-based precision soil sampling strategies have seen increased adoption in the last decade among consultants and growers in the US (Walton et al., 2010). Grid soil sampling consists of placing uniformly sized grids – ranging in size from 1.0 to 5.0 ha – in a field. Composite soil samples are then collected within each grid to be representative of that particular area of the field.

Currently, various precision soil sampling methods are utilized throughout the southeastern US by consultants, precision ag companies, and growers to determine spatial nutrient variability and inform variable-rate fertilizer applications. The most common among these strategies is the grid-based approach - most commonly used are 1.01- and 2.02-ha grids – due to its ease of implementation and eliminating the need for requiring any prior field knowledge or expertise of any specialized software. Wollenhaupt and Wolkowski (1994) found that grids should be no larger than 0.40 ha to capture the spatial nutrient variability. They also found that grid-based sampling produced maps with higher accuracy when compared to zone-based sampling. Several studies have also investigated the possibility of utilizing management zones (MZ) for soil sampling in the past, including using layers such as farmer experience and aerial imagery (Fleming et al., 2000), stable yield maps from multi-year yield data (Flowers et al., 2005), topography, and electrical conductivity (EC) (Johnson et al., 2003). Farmer experience and soil color maps created from aerial imagery identified homogeneous subregions within fields, but the effectiveness of these strategies varied across different fields (Fleming et al., 2000). Flowers et al. (2005) found multi-year yield maps nearly as effective at delineating soil nutrient variability as a 1.01-ha grid. Johnson et al. (2003) investigated the use of EC and found no consistent relationship between EC and yield variability. However, the addition of other data layers could be used to establish MZs, correlating with crop yield. Previous work in this area has primarily been conducted in the Midwestern United States where soil type and cropping systems differ considerably from the southeastern US. Limited research on different precision soil sampling approaches is available in the prevalent soil types in the southeastern US.

The adoption and utilization of different precision soil sampling strategies vary considerably among growers, especially in the southeastern US (Mooney et al., 2010). The selection of an appropriate grid size or management zone further differs among the users depending on several factors. Common questions received from consultants and growers are about the optimal grid size for soil sampling and the type of information needed to implement soil sampling based on management zones. While grid-based soil sampling is easier to implement and widely used in the southeastern US, it can become labor-intensive and costly depending on the size of the grids. Similarly, zone-based soil sampling can decrease the number of samples taken from a field; however, the exact approach to defining and validating zones becomes difficult and overwhelming. A study comparing the different grid and zone-based precision soil sampling methods is needed to provide unbiased, research-based information to consultants and growers for determining a practical and cost-effective soil sampling strategy for their farms.

1.2 Literature Review

1.2.1 Precision Agriculture

The International Society of Precision Agriculture defines precision agriculture as a management strategy that gathers, processes, and analyzes temporal, spatial, and individual data and combines it with other information to support management decisions according to estimated variability for improved resource use efficiency, productivity, quality, profitability and sustainability of agricultural production (ISPA, 2022). Precision agriculture includes four key elements: global positioning system (GPS), gathering information, decision support, and variable-rate treatment (Pedersen & Lind, 2017). The ultimate reason for precision agriculture research and development is due to the amount of spatial variability of soil types, nutrients, yield, etc. This issue is by no means a new problem for agricultural production; however, it is more prominent now as advancements in engineering and equipment have allowed for far more land to be covered by one machine per day. Precision agriculture technologies have been commercially available since the 1990s, though the adoption of these practices has been slow in the southeastern US (McBride & Daberkow, 2003). With advancements in technology, such as yield monitoring, precision soil sampling, variable-rate, and remote sensing, the adoption of precision agriculture practices is increasing on both small and larger farms (Lambert et al., 2015). Stafford (2000) mentions that precision agriculture is an important step ahead for growers to reduce costs by making data-driven decisions. Pedersen and Lind (2017) described the adoption of precision farming practices as a "step back in time" referring to the idea that as fields and equipment grow larger, the amount of land one grower can manage gets increasingly large. With the help of remote sensing and other precision techniques today, growers can effectively manage these large farms with detailed knowledge about each field just as our ancestors did when farming small areas by hand.

1.2.2 Components of Precision Agriculture

Precision agriculture can be described as a toolbox with a different set of tools that can be used for different jobs/operations based on the farm size and crop management practices. Many authors have described that precision technologies have benefitted different agricultural practices in some way. Many of these technologies are or are related to, remote sensing, crop monitoring, planting, spraying, yield monitoring, and site-specific applications (Adamchuk et al., 2004; Gebbers & Adamchuk, 2010; Khan et al., 2021; Lambert et al., 2015; Lowenberg-DeBoer & Erickson, 2019; McBride & Daberkow, 2003; Mooney et al., 2010; Stafford, 2000; Walton et al., 2010).

Remote sensing can be described as the use of a sensor carried by satellite or unmanned aerial vehicle (UAV) to collect data (Mulla, 2013). Proximal sensing is very similar, except the sensor is within relative proximity to the object being sensed and sometimes even in contact with the object such as a crop sensor attached to a sprayer boom (Mulla, 2013) or a soil moisture sensor placed in the field (Adamchuk et al., 2018). Remote and proximally-sensed information can be used during the growing season to determine crop health (Ferguson & Rundquist, 2018), spatially map weed density in a field (Sishodia et al., 2020), create water and nutrient recommendations (Basso et al., 2016; Lacerda et al., 2021), and even survey soils and topography (Escadafal, 1993; Guo et al., 2012; Hurley et al., 2001).

Planting technology has advanced rapidly as well, from ground-driven seed meters and gravity seed tubes to fully electronic meters and precision delivery systems (Strasser et al., 2019). A few of the major advancements in planter technology have been the development of electric row units for more precise seed metering and individual row-control for variable-rate seeding (Virk et al., 2020), hydraulic and pneumatic downforce (Virk et al., 2021), and on-the-go sensing of soil properties to vary seeding rate and depth in real-time (René-Laforest et al., 2014).

The size and availability of technology on agricultural sprayers have also advanced considerably. Most advanced sprayers on the market today have at least 30 or 36 m boom and come equipped with a rate controller and section control system (Sharda et al., 2013). Advanced spray technologies such as pulse width modulation (PWM) systems (Butts et al., 2019; Virk and Meena, 2022), are also becoming more standard options on new agricultural sprayers. The most precise sprayer on the market today has a series of cameras that are looking ahead of the sprayer boom and can identify weeds in the field and instantly turn on the correct nozzles to spray only the areas of the field where weeds are present (Heraud, 2018).

Yield monitoring has become one of the most widely used aspects of precision agriculture (Lowenberg-DeBoer & Erickson, 2019). Yield monitors use a combination of GPS and various sensors to determine the amount of crop harvested from a given location in the field. This data can then be analyzed using a geographic information system (GIS) to help a grower make management decisions for the following year (Fulton et al., 2018). Yield data is much like a report card at the end of a year that helps in assessing the performance of different management decisions made throughout the growing season.

For each of these components and technologies mentioned above, the spatial resolution of data being collected or the precision of the application being conducted has increased considerably from the field level to in some cases plant-by-plant level. The advancements in these technologies and the data quality have greatly improved the capabilities of site-specific applications (Sharda et al., 2018). These improvements include site-specific application of water (Evans et al., 2013), seed (Virk et al., 2020), tillage (Bertocco et al., 2008), and soil amendments or nutrients (Dobermann et al., 2002). Precision placement of these inputs combined with the right application rate and timing during the season have attributed to increased input-use efficiencies and crop yields.

1.2.3 Site-Specific Nutrient Management

1.2.3.1 Traditional soil sampling and uniform fertilizer application

In previous studies, many authors have stated that the recommendation for soil sampling a field was to only sample areas that are representative of the area being sampled (Mahler & Tindall, 1994; Sabbe & Marx, 1987; Wollenhaupt & Wolkowski, 1994). In traditional composite soil sampling, soil samples collected from random locations throughout the field are combined to create one or two composite samples for the whole field and sent for soil analysis. The soil test results are then used to perform single-rate, uniform fertilizer applications. With the introduction of precision agriculture and VR technology, more growers have slowly transitioned to utilizing a more systematic approach i.e. some sort of precision soil sampling to inform site-specific nutrient applications.

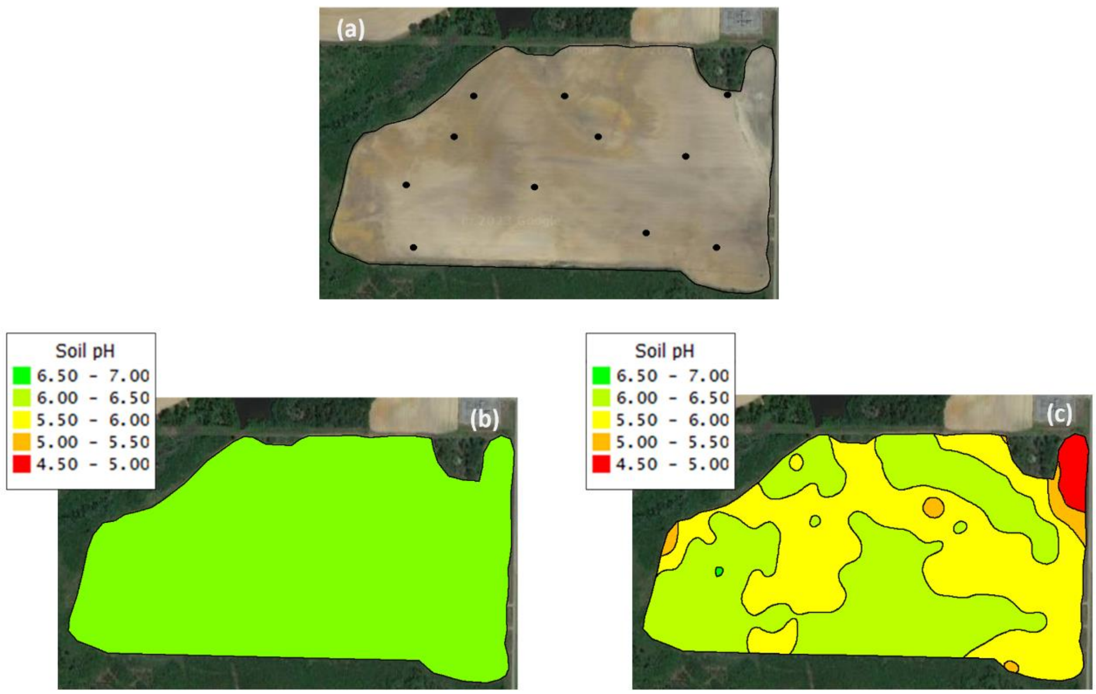

Figure 1.1 Illustration of (a) composite soil sampling method, (b) soil pH map based on the composite soil sampling, and (c) map depicting the actual pH variability in the field.

1.2.4 Precision Soil Sampling Strategies and VR Fertilizer Application

1.2.4.1 Grid Soil Sampling

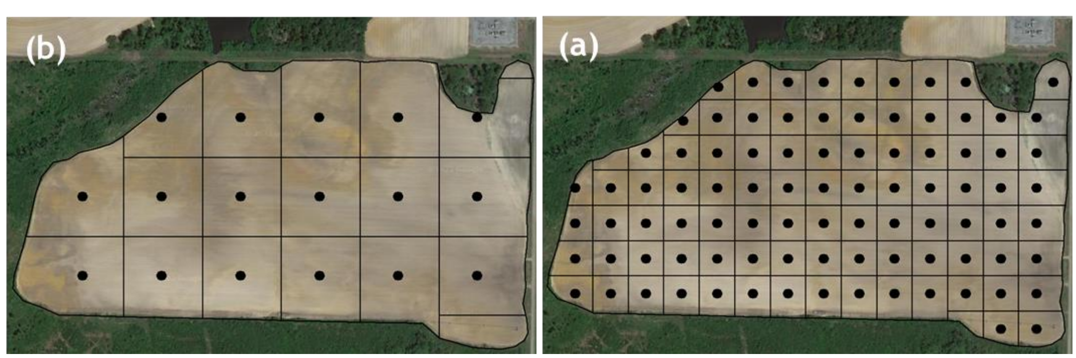

Figure 1.2 Maps illustrating grid soil sampling method on (a) 0.40-ha and (b) 2.02-ha grids for a field.

Many studies have been conducted to evaluate the appropriateness of soil sampling methods to effectively display the spatial distribution of soil nutrients (Brouder et al., 2005; Flowers et al., 2005; Mahler & Tindall, 1994; Mallarino & Wittry, 2004; Stępień et al., 2013). Before the initial adoption of grid soil sampling, traditional soil sampling was one of the most common methods to determine soil nutrient requirements. In some cases, the fields were also soil sampled by dividing them into sections of similar productivity or soil type based on farmer knowledge of the field (Mahler & Tindall, 1994). With the advancement of GPS and soil sampling technologies over the years, most growers and consultants in the southeastern US have transitioned to grid soil sampling, where uniform-sized grids are overlayed on the field and soil samples are collected from each grid. An illustration of grid soil sampling on two different grid sizes is shown in Figure 1.2. The sampling grid size is an important consideration for the grid sampling strategy. Different grid sizes have been evaluated by the researchers ranging from 0.2- to 4-ha and findings from these studies varied depending on the location and environmental factors (Brouder et al., 2005; Flowers et al., 2005; Mallarino & Wittry, 2004; Stępień et al., 2013; Wollenhaupt & Wolkowski, 1994).

Wollenhaupt and Wolkowski (1994) reported that a grid size of approximately 0.4 ha (200ft x 200ft) should be used during the first year to determine in-field nutrient variability, and some additional sampling should be conducted in the areas of the field where nutrient levels are either too high or too low. The authors suggested a “systematic unaligned sampling approach” to be used, where smaller grids are created inside the coarse grids to create randomization in the sampling locations. Mallarino and Wittry (2004) reported a

0.2-ha grid size can produce a very detailed map of soil nutrients although it is not practical because of the high cost and increased time associated with collecting the increased amount of soil samples. This study also found that the amount of spatial variability influenced the effectiveness of the method used for soil sampling. When compared to a 0.2-ha grid sampling method, a grid size of 1.2−1.6 ha produced VR prescription maps that, on average, accurately placed P and K fertilizers on 54 % and 66 % of the field, respectively. Flowers et al. (2005) concluded that grid cell sampling results in higher amounts of variability explained when compared to grid point sampling, while the use of high-intensity grid point samples was used to create the grid cell method. Stępień et al. (2013) found that for lime, P, and K, a 2-ha grid sampling method was able to explain more variability than a 4-ha grid sampling method. Most of these studies show that there is not one single grid sampling approach that is optimal for all fields and soil properties, which makes choosing the correct approach more challenging especially when no sampling has been conducted previously in a field. Sabbe and Marx (1987) stated that sampling should aim to increase the precision and accuracy of nutrient variability with the least number of samples. Varying results among these studies require more investigation in this area, especially when the location and dominant soil types change.

1.2.4.2 Soil Sampling Based on Management Zones

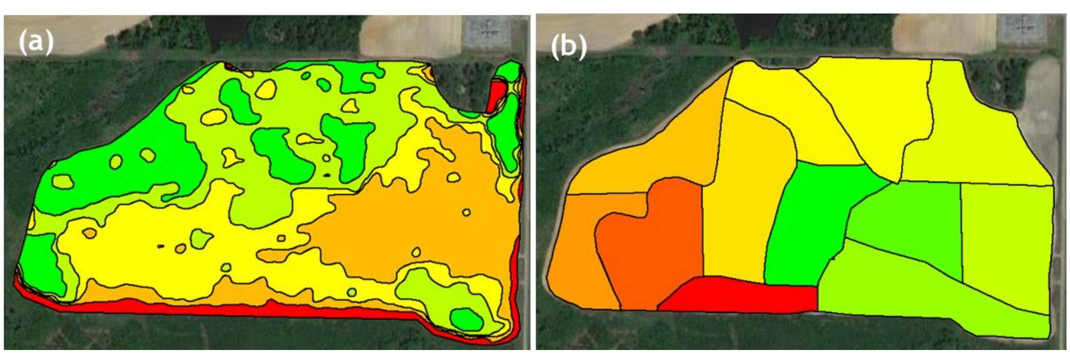

Figure 1.3 Depiction of management zones created from (a) soil brightness and (b) historical field knowledge and yield history for zone soil sampling.

Management zones (MZs) are defined as areas of homogeneous properties in a single field that can be managed as separate smaller fields (Shaner et al., 2008). The overall goal of MZs is to reduce the total amount of sampling locations while maintaining a high level of variability captured. The increased amount of technology development and digital tools available today has allowed the research in this topic area to be very broad (Khanal et al., 2020). Delineation of MZs typically starts with one or more spatial data layers to subdivide the field into non-uniform-sized areas. Many previous studies have investigated the suitability of different spatial data layers to create these MZs such as soil survey data, EC, topography, aerial imagery, yield, farmer knowledge, and other remote sensing approaches (Castrignanò et al., 2018; Fleming et al., 2000; Flowers et al., 2005; Gavioli et al., 2019; Hornung et al., 2006; B. Iticha and C. Takele, 2019; Johnson et al., 2003; Li et al., 2008; Mallarino & Wittry, 2004; Nawar et al., 2017; Schepers et al., 2004; Shaner et al., 2008).

Fleming et al. (2000) evaluated the use of soil color, topography, and farmer experience to create MZ for VR nitrogen to compare to a grid sampling scheme. The authors found no significant differences in yield between the two methods and concluded that the MZ strategy is effective because it was cheaper to implement than the grid method. Johnson et al. (2003) reported that the use of EC data exclusively to create MZ is ineffective, and the addition of complementary data layers, such as yield could benefit the actual depiction of soil nutrient variability. The findings of Mallarino and Wittry (2004) agreed with Johnson that multiple spatial data layers create effective MZs. Schepers et al. (2004) used principal component analysis to create management zones from soil brightness, elevation, and EC and reported it as an effective approach in delineating MZs to characterize soil chemical properties.

Flowers et al. (2005) created MZs from multi-year yield data and found that this method is nearly as effective as a 98-m grid method while reducing sampling time and cost. Although Hornung et al. (2006) found MZs based on soil color performed better than the yield in a study comparing soil color, topography, and farmer knowledge MZ, and yield-based MZ including soil imagery, organic matter, cation exchange capacity, soil texture, and yield. These results also show that adding more spatial data layers doesn't necessarily increase the resolution of the soil nutrient map. Shaner et al. (2008) compared different MZs to grid soil sampling and concluded that zone-based soil sampling could be a cost-effective method. Li et al. (2008) evaluated the use of fuzzy c-means clustering for creating MZs with EC, yield, and normalized difference vegetation index (NDVI). The authors reported this approach to be a good option for creating initial MZs for soil sampling. An extensive literature review by Nawar et al. (2017) pointed out several research gaps in MZ creation. The authors concluded that a single spatial data layer is not sufficient for explaining enough variability to base all management decisions, and the use of new remote sensing methods should be researched for more effective and accurate MZs.

With continued research on MZ delineation, there is also a disconnect between the researcher's and the grower's ability to create or use them effectively. The process of creating informative and accurate MZ maps is difficult, especially when multiple layers are being used. Growers can produce MZs by hand drawing on aerial maps based on their knowledge of the field (Fleming et al., 2000; Oliver et al., 2010), but this is time-consuming when doing so in multiple fields and nearly impossible if they have no historical knowledge about the field. Currently, many precision agriculture companies also offer specialized software that can be used for the delineation of MZs. Each of these companies has a specific approach to help determine the best MZs and identify areas for soil sampling that may include a combination of soil EC and topography maps, topography, crop health (NDVI), or gamma radiation emitted from the soil from previous years. While the approach for delineating MZs may differ amongst these companies, many of them claim to decrease the overall number of soil samples needed compared to grid soil sampling while increasing the accuracy of input applications. Most of these software providers are also based and operated out of the midwestern US where these approaches have been tested primarily in the soils common to those production areas. Due to grid soil sampling still being one of the most predominant soil sampling methods in the southeastern US, utilization of the software and services provided by these companies for zone soil sampling are minimal to none. The large inherent spatial soil variability in the southeastern soils along with the high costs and time associated with grid soil sampling approaches necessitate an exploration into different zone soil sampling strategies. An investigation into the utility and effectiveness of the commercially available software for zone soil sampling is also needed to determine cost-effective and efficient precision soil sampling strategies that can be utilized by consultants and growers across the southeastern US.

1.2.5 Variable-Rate Application

VR application of crop inputs is one of the key components of precision agriculture allowing for site-specific placement of crop inputs to increase overall productivity (Pedersen & Lind, 2017). VR application support the 4Rs of nutrient management regarding the right rate and right place (IPNI, 2022). Single-rate fertilizer applications can result in over- and under-application in certain areas of the fields. This also leads to environmental concerns (Liakos et al., 2013) where over-application of certain fertilizers could be subject to runoff into waterways that are harmful to aquatic life and drinking water supplies. Additionally, single-rate fertilizer applications can also be uneconomical as correct placement of input is not met in all areas of the field and economic return, measured by plant response in yield, may be low in an area that either received too much fertilizer or not enough (Sawyer, 1994; Wittry & Mallarino, 2004; Yang et al., 2001).

The technologies discussed previously such as sensing and yield monitoring can influence applications of soil amendments and/or nutrients if a grower is quite progressive (Lambert et al., 2015). Although many site-specific nutrient applications are informed by soil sampling (Sabbe & Marx, 1987; Sawyer, 1994; Wollenhaupt & Wolkowski, 1994). Wollenhaupt and Wolkowski (1994) found that VR applications for site-specific nutrient management are only as accurate as the soil sampling data they are created from. This implies that if the data being used to create the VR prescription map is inaccurately representing the nutrient levels in certain areas of the field, the VR application may not be correcting the spatial variability issue but could be making it even worse. Sawyer (1994) suggested that economic return to VR applications does not occur in every field and every application because of factors such as sampling strategy and little response in crop yield. However, when conducted appropriately, VR application of crop inputs has the potential to increase productivity in most fields (Bullock et al., 1994; Franzen & Peck, 1995; Sawyer, 1994).

1.3 Rationale

While many previous studies have investigated different aspects related to grid soil sampling, the optimal sample density recommendation has varied. Additionally, most of these studies focused on precision soil sampling methods have been conducted in the midwestern US. Limited research and information are available on the effectiveness and economics of different grid sizes for grid-based soil sampling approaches in the southeastern US. One common theme concerning grid soil sampling is that smaller grid sizes are more accurate in depicting spatial nutrient variability within the fields; however, they are not effective in terms of both time and cost. For zone soil sampling, a review of the literature suggests that there are many ways to create MZs for zone soil sampling and the results again vary considerably among the type of spatial data layers used and between different regions. Today, data quality is increasingly becoming more important in every aspect of precision agriculture due to the increased interest among the growers to make informed, data-driven decisions, and improve efficiencies and productivity in their farming operations. Data quality in regards to precision soil sampling and the accuracy of VR fertilizer applications is also gaining interest, which is evident from the increased questions and concerns from growers and consultants around the suitability of different commonly-used precision soil sampling strategies and their effectiveness in the southeastern US. To answer these questions, it is imperative to compare different grid and zone soil sampling strategies and investigate their efficacy and economics as they relate to the accuracy of site-specific nutrient management in the southeastern soils. The broader impact of the proposed research involves not only growers but the whole precision agriculture industry in the southeastern US including crop consultants, fertilizer retailers, agricultural technology software, and service providers. This research will provide valuable information about the data quality and accuracy associated with different precision soil sampling strategies and how some of the currently utilized methods can be improved upon to capture within-field spatial nutrient variability and increase the accuracy of VR fertilizer applications.

The overall goal of this research study is to compare and evaluate different precision soil sampling strategies − grid and zone − to determine an effective and economical soil sampling method(s) that accurately represents the nutrient spatial variability within the fields and can be utilized by agricultural producers and consultants for site-specific nutrient management in the southeastern US.

1.4 Objectives

Based on the literature of review presented here and the information known about different precision soil sampling strategies, the following objectives were formulated for this research:

Objective 1: To evaluate the effectiveness of different commonly-used grid sizes for precision soil sampling in depicting within-field spatial nutrient variability and perform an economic comparison among different grid sizes.

Objective 2: To compare and investigate different zone-based management strategies for precision soil sampling and evaluate their effectiveness as compared to the grid soil sampling methods.

CHAPTER 2

EFFICACY AND ECONOMICS OF DIFFERENT SOIL SAMPLING GRID SIZES FOR SITE-SPECIFIC NUTRIENT MANAGEMENT IN THE SOUTHEASTERN US[1]

[1] Tucker, M., Virk, S., Harris, G., Levi, M., Lessl, J., Smith, A., Kichler, J., McAllister, S., Hand, J., Carlson, S., and Sapp, P. Submitted to Precision Agriculture, 11/16/2023.

2.1 Abstract

Precision soil sampling on uniform-sized grids is a widely adopted practice for site-specific nutrient management in the southeastern United States. To address questions and concerns from growers regarding optimal grid size for soil sampling, a study was conducted across nine fields in 2022 to evaluate the influence of different grid sizes on the depiction of spatial nutrient variability, and their influence on the accuracy of variable-rate fertilizer application and total application costs. Soil sampling was conducted in each field using grid sizes of 0.4, 1.0, 2.0, 3.0, and 4.0 ha, and the resulting variable-rate prescription maps for lime, P, and K were compared with a reference map (generated from high-density soil sampling; approximately 2.5 samples per hectare) to assess nutrient application accuracy. An economic analysis was also conducted including the soil sampling costs, soil analysis costs, and nutrient costs to determine the effect of grid size on total application costs. The study results indicated that soil sampling on a 0.4 ha grid size performed the best in depicting the spatial variability of soil pH, P, and K within the fields and exhibited the highest application accuracy for the variable-rate prescription maps. The general trend was that the application accuracy decreased with an increase in grid size with the potential for under- and over-application of nutrients significantly increasing at the larger grid sizes of 2.0 ha or greater. For economic analysis, the total application cost varied among the fields as it was largely influenced by the amount of under- and over-application associated with each grid size. In most fields, the total application costs for a 0.4 ha grid size were lower or comparable to other grid sizes. In some fields, the larger grid sizes exhibited lower application costs but at the expense of reduced application accuracy. Overall, the findings

from this study suggested that the smaller grid sizes were most optimal for soil sampling providing both accuracy and cost-effectiveness for site-specific nutrient management.

2.2 Introduction

Spatial variability within agricultural fields is a major challenge in row crop production, especially in the southeastern United States. This variability can be related to many factors including topographical features, soil properties - both physical and chemical - and previous management history (Mulla & McBratney, 2002). This within-field spatial variability leads to crop variability which can be observed in stand development, crop health, maturity, and ultimately yield. While both soil and crop variability make crop management challenging; one of the main principles of precision agriculture is to accurately detect and address this variability using various practices and technologies (Sawyer, 1994). If the spatial variability is under- or over-assessed, the potential of inaccurate applications of crop inputs in certain areas of the field is increased and can further lead to crop variability within the field. Variable-rate (VR) application of inputs, such as fertilizer and water, is the primary mechanism to address this within-field spatial variability and to inform site-specific crop input management in precision agriculture (Stafford, 2000). With advancements in sensing and application technologies in recent years, new and improved methods of site-specific crop input management have been developed and adopted by growers. These precision practices help growers to be more efficient and sustainable while also improving productivity to feed the growing population (Gebbers & Adamchuk, 2010), which is expected to reach 9.8 billion globally by 2050 (Nations, 2017).

Among different site-specific management strategies used by growers, variable-rate fertilizer applications to address within-field nutrient spatial variability is a widely adopted practice in precision agriculture (Lowenberg-DeBoer & Erickson, 2019). One of the most important aspects of site-specific nutrient management is proper soil testing to determine varying soil nutrient levels within the fields. Soil sampling approaches have evolved from collecting few samples based on grower knowledge or management history to precision soil sampling techniques such as collecting samples from certain size grids and pre-defined zones within a field. Before the adoption of any precision soil sampling methods, composite soil sampling to determine soil nutrient levels within the fields was a common practice (Mahler & Tindall, 1994). Composite soil sampling consists of collecting multiple soil cores from randomly selected locations across the field or sections of similar productivity or soil type based on prior knowledge, and then combining them to create a single composite sample for each field or each sub-area within the field. The soil testing results from composite samples are used to apply lime or fertilizer at a single rate uniformly across the whole field. While the composite soil sampling and single-rate fertilizer application approach are relatively easy to implement, it usually results in relatively large areas of under- and over-application of fertilizer within the fields, thus causing more nutrient variability issues (Sawyer, 1994). To properly address nutrient spatial variability within the agricultural fields, grid- and zone-based precision soil sampling strategies have become more common in the last decade among consultants and growers in the US (Walton et al., 2010). A grid soil sampling approach consists of placing uniformly sized grids within a field, which can range from 1.0 to 5.0 ha in size. Composite soil samples are then collected within each grid to represent that particular field area (Wollenhaupt & Wolkowski, 1994).

A variety of methods for collecting samples within the grids have been investigated including zigzag pattern, grid cell sampling (random locations from the entire grid), and grid point sampling (random locations within a 3-meter radius of the center point) (Mahler & Tindall, 1994; Sabbe & Marx, 1987). Contrary to grid sampling, zone-based soil sampling involves using various soil and crop features, remotely sensed information, farmer knowledge, and/or other spatial data (Flowers et al., 2005; Hornung et al., 2006; Schepers et al., 2004) to delineate homogenous areas within the field and collect samples from each area. While both grid and zone soil sampling methods are commonly utilized, each method has its own merits and drawbacks. Grid-based soil sampling is easier to implement; however, the accurate representation of the spatial nutrient variability in the field depends largely on the selected grid size (Sawyer, 1994). Zone-based sampling can be challenging to implement because of the need for more advanced knowledge and experience in analyzing spatial data layers; however, if conducted appropriately it can reduce the number of soil samples while improving the amount of nutrient variability captured within the fields (Fleming et al., 2000). Besides the accurate depiction of spatial nutrient variability, the cost associated with each soil sampling method is also an important consideration. While grid soil sampling at higher densities, to capture more variability, increases overall sampling and analysis costs due to a large number of soil samples, zone sampling strategies can also become costly depending on different types of spatial data used and the amount of analysis required to accurately delineate management zones. Generally, the number of samples collected in zone sampling is considerably lower than in grid sampling. While both grid and zone sampling are valid methods, grid sampling remains one of the most widely used approaches for soil sampling by growers and consultants, especially in the southeastern US; largely due to its ease of implementation and the fact that it does not require any historical field information.

Several studies have evaluated the appropriateness of different grid soil sampling methods in effectively representing the spatial distribution of soil nutrients (Brouder et al., 2005; Flowers et al., 2005; Mahler & Tindall, 1994; Mallarino & Wittry, 2004; Stępień et al., 2013). Different grid sizes, ranging from 0.2- to 4.0-ha, have been investigated by many researchers and reported varied findings depending on the geographic location and other environmental factors associated with the agricultural fields (Brouder et al., 2005; Flowers et al., 2005; Mallarino & Wittry, 2004; Stępień et al., 2013; Wollenhaupt & Wolkowski, 1994). Wollenhaupt and Wolkowski (1994) reported that a grid size of 61 x 61 m (roughly 0.4 ha) should be used during the first year to determine soil nutrient variability, along with some additional sampling in areas of the field with very low or high nutrient values. The authors also suggested utilizing a "systematic unaligned sampling approach", where smaller grids are created inside the coarser grids to generate randomization within the sampling locations. Mallarino and Wittry (2004) reported that a 0.2-ha grid can produce a very detailed map of soil nutrients, although it is not practical because of the high cost and increased time associated with collecting a large number of soil samples. The authors also found that the amount of spatial variability influenced the effectiveness of the soil sampling method. When compared to a 0.2-ha grid sampling method, a grid size of 1.2-1.6 ha produced VR prescription maps that, on average, accurately placed P and K fertilizers on 54 and 66 percent of the field (area), respectively. Flowers et al. (2005) concluded that grid cell sampling (soil sampling from random locations within the entire grid) resulted in a higher amount of nutrient variability captured compared to grid point sampling (soil sampling within 3 m of the grid center). Stępień et al. (2013) reported that a 2-ha grid sampling method was able to explain more variability in soil pH, P, and K than a 4-ha grid sampling method. Brouder et al. (2005) concluded that a 1.0 ha grid is only 10% better than whole-field composite sampling. The authors also observed small differences in the spatial nutrient maps created using inverse distance weighted (IDW) and kriging interpolation methods but suggested that no major consequence exists to using either interpolation method. Most of the previous research indicates that when it comes to the grid sampling approach, a single grid size may not be optimal for all fields or soil types, which makes it more challenging to choose the correct approach especially when no prior soil sampling has been conducted. These studies have been conducted in different regions of the US and reported varying results mainly due to the different soil types and crop management practices prevalent within each region. Sabbe and Marx (1987) stated that the goal of soil sampling should be to increase the precision and accuracy of nutrient variability with the least number of samples. This is even more important today due to the increased prices of fertilizer and other crop inputs. Basso et al. (2006) suggested that site-specific nutrient management of nitrogen fertilizer has both environmental and economic benefits. Inaccurately depicting nutrient variability in crop fields is found to be one of the main reasons for VR applications not being profitable (Sawyer, 1994). While grid soil sampling can be costly due to the number of samples needed to produce accurate prescription maps, (Fleming et al., 2000; Koch et al., 2004), data quality is an important consideration for VR applications to be accurate and effective (Fleming et al., 2000; Sawyer, 1994).

While many previous studies have investigated different aspects related to grid soil sampling, most researchers have reported that the soil sampling results can vary depending on the geographic location and other soil and crop management practices specific to the region. Most of the previous studies focused on precision soil sampling having been conducted in the midwestern US and some in other countries with minimal to no published information in the southeastern US. Current research on evaluating the effectiveness of different grid sizes to determine an optimal and economical grid sampling approach in the southeastern US is limited. Data quality is increasingly becoming more important in every aspect of agriculture today due to the increased adoption of technology among growers and the rising interest in being more efficient with crop inputs. With the rising input costs and narrow profit margins, growers are interested in making more informed, data-driven decisions to improve efficiency and productivity in their farming operations. Due to varying cropping systems and prevalent production practices in the southeastern US, questions from growers and consultants around the suitability and efficacy of different grid sizes for precision soil sampling, and how it affects the application accuracy and economics of VR fertilizer application are common. To investigate these concerns and effectively answer questions related to soil sampling grid size, this study was conducted to evaluate the efficacy and economics of different commonly used grid sizes for precision grid-based soil sampling in the southeastern US. The specific objectives of this study were: (1) to compare and evaluate the effectiveness of different grid sizes in depicting soil nutrient variability and their influence on fertilizer application accuracy, and (2) to perform an economic analysis among different grid sizes to determine a cost-effective soil sampling strategy (or strategies) that also ensures high application accuracy.

2.3 Materials and Methods

Data for this on-farm study was collected in 2022 across nine different grower fields to be planted in row-crops prevalent in the southeastern US (cotton, corn, or peanuts). The selected fields ranged from 8.3 to 37.6 ha in size. All fields were located in the Coastal Plain physiographic region of the southeastern US and had two or more soil types. Detailed information on the location, size, and soil types present within each field is presented in Table 2.1 (Web Soil Survey, 2021). These fields were randomly selected by local county Extension agents with the only criterion that the field be representative of the local geographic area. The soil sampling methods and other procedures were kept consistent among all locations used in this study.

Table 2.1 Location and size of all nine fields used in this precision soil sampling study conducted in 2022.

Field	Latitude	Longitude	Size (ha)	Soil Type(s)
1	32.880897	-82.20426	9.1	Tifton, Dothan, Carnegie, Grady
2	31.307355	-83.914703	37.6	Tifton, Carnegie, Leefield, Borrow
3	31.077626	-83.694082	9.1	Dothan, Tifton
4	33.209401	-82.503499	36.9	Faceville, Tifton, Orangeburg, Nankin
5	32.045822	-84.377226	12.4	Greenville, Tifton, Ochlockonee
6	32.043561	-84.365362	8.3	Greenville, Tifton, Ochlockonee
7	31.729895	-84.463742	25.5	Greenville, Grady
8	31.473537	-83.407591	22.4	Ocilla, Clarendon, Alapaha, Tifton
9	31.535035	-83.659815	12.7	Tifton, Carnegie

2.3.1 Grid Soil Sampling

Field boundaries for all fields were imported into a farm data management software (SMS Advanced, AgLeader Technology, Ames, IA) and soil sampling maps were created using grid sizes of 0.4, 1.0, 2.0, 3.0, and 4.0 ha (1.0, 2.5, 5.0, 7.5, and 10.0 ac) as shown in

Figure 2.1 for one of the fields used in this study. Each sampling grid was independent of the others (i.e., no sample was used for multiple grid sizes). Sampling points were placed at the center of each grid for ease of navigation to the center of the grid during soil sampling. The soil sampling maps were uploaded on a handheld Trimble GPS unit, with a horizontal accuracy of 2-4 meters, (Nomad 1050, Trimble Inc., Sunnyvale, CA), which was used to navigate to different soil sampling grids within each field.

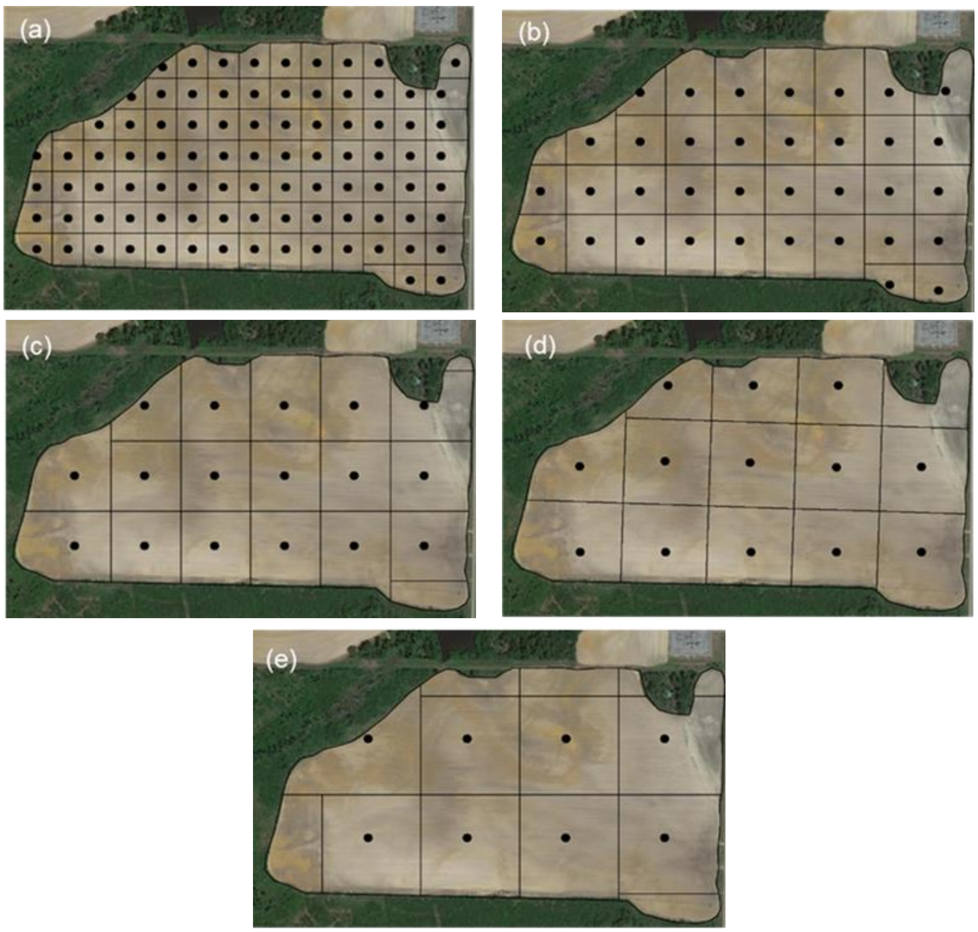

Figure 2.1 Soil sampling maps at grid sizes of (a) 0.4 ha, (b) 1.0 ha, (c) 2.0 ha, (d) 3.0 ha, and (e) 4.0 ha for one of the fields used in this study.

In all fields, soil samples were collected, in November through January, at each grid size using the point sampling method which involved collecting 12 to 15, 15.2 cm deep cores in a 6.1 – 9.1 m radius around each point, and then combining all the cores to make a composite sample which represented that particular grid. All soil samples from each field were placed in a pre-labeled paper bag with the field and sample number. Once all the samples were collected, they were sent to the University of Georgia's Agricultural and Environmental Services Laboratories (AESL) in Athens, GA for soil nutrient analysis. The AESL used Mehlich 1 extractions to determine soil nutrient levels and provided the analysis for soil pH, Phosphorus (P), Potassium (K), Calcium (Ca), Magnesium (Mg), Zinc (Zn), Manganese (Mn), and cation exchange capacity (CEC) for each sample in a .csv format. Since this study focused on soil pH, P, and K, soil test results for only those nutrients were used for further mapping and analysis.

2.3.2 Spatial Nutrient Mapping and Analysis

Soil nutrient analysis results for each field were imported into AgLeader SMS Advanced software and used for further spatial analysis and interpolation. For all fields, spatial maps for soil pH, P, and K were created from soil nutrient levels for each grid size using an inverse distance weighting (IDW) interpolation method. The IDW interpolation uses an algorithm to predict values of unmeasured locations by weighting measured values based on the spatial distance from the measured locations (Burrough et al., 2015). The interpolation process consisted of creating a 9.14 x 9.14 m raster map for each grid size. Each cell in the map was georeferenced and contained soil nutrient values for soil pH, P, and K. The soil analysis results for all sampling methods i.e. grid size of 0.4, 1.0, 2.0, 3.0, and 4.0 ha were combined to replicate a high-density sampling method (approximately 2.5 samples per hectare), which was assumed to represent the actual spatial variability within each field, and was also used as a reference layer for comparison among the maps based on different grid sizes. This high-density map is hereafter referred to as the reference map for each nutrient. The VR lime, phosphorus (P_2O_5), and potassium (K_2O) prescription maps were created for each grid size strategy for fertilizing cotton for a yield goal of 1345 kg ha^{-1} using the UGA cotton fertilization recommendations (Plank and Harris, 2022). All fertilizer prescription maps were converted to raster format to enable direct comparison to the actual prescription map for each nutrient. A comparison between the prescription map for each grid size and the reference prescription map was performed to create a difference map that depicted the spatial location (total area receiving each prescribed fertilizer amount) as well as the amount of under- and over-application that would occur in those areas in the field. Figure 2.2 illustrates an example of this methodology where (a) is the reference P map for the field depicting actual (assumed) nutrient variability within the field, (b) is the prescription map generated from soil sampling results from a 2.5 ac grid size, and (c) is the difference map which represents the areas of on-target (green), under- (red) and over-application (blue) within the field.

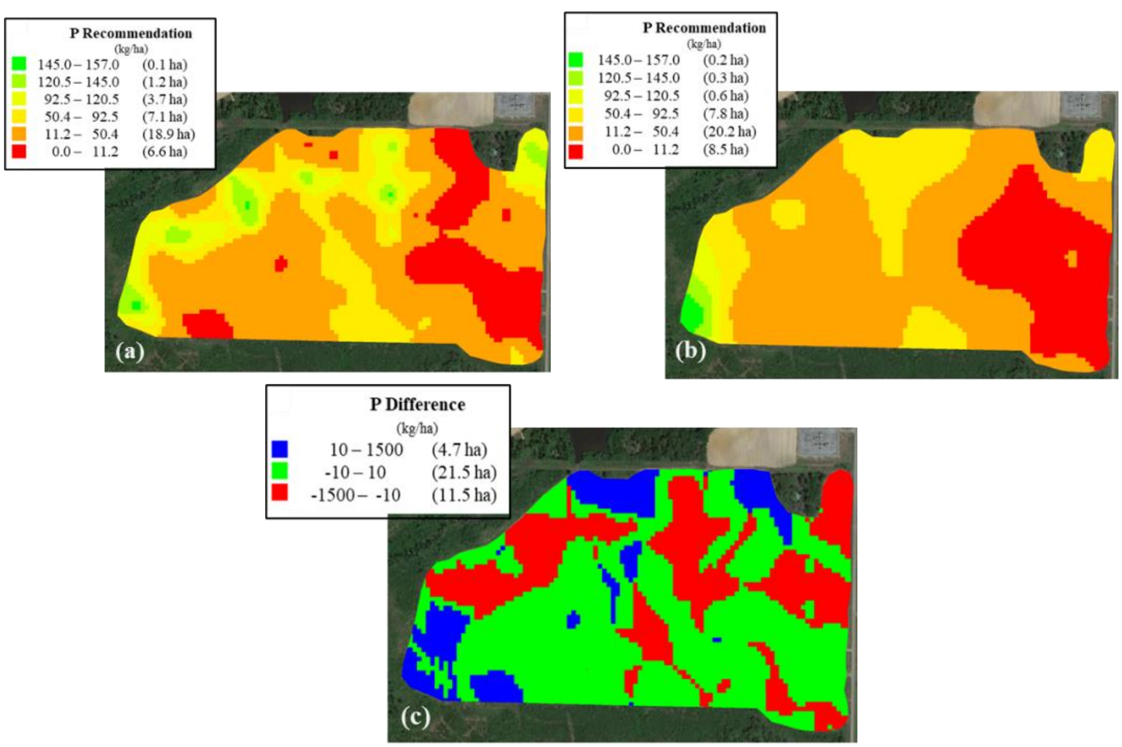

Figure 2.2 Illustration of a (a) prescription map for P based on reference nutrient variability, (b) prescription map generated from 2.5 grid size sampling, and (c) difference map. In (c), the areas in green represent a portion of the field that received accurate/on-target fertilizer application whereas the areas in red and blue represent under- and over-fertilized areas, respectively in the field.

2.3.3 Economic Analysis

For each field, an economic analysis was conducted to determine the total cost per hectare for the sampling strategy based on each grid size. The total amount of recommended fertilizer for each grid size was computed from the VR prescription maps for lime, P, and K. The lime and fertilizer costs ($ kg^{-1} of fertilizer) were obtained from the 2022 UGA Enterprise Row Crop Budgets (Zhou et al., 2022). The actual prices used for this analysis were as follows: lime – 0.055 ($ kg^{-1}), Phosphorus – 1.47 ($ kg^{-1}), and Potassium – 1.50 ($ kg^{-1}). The soil sampling costs were calculated based on the nominal soil sampling fees charged by the consultants in the southeastern US. This cost was determined to be $20 per hectare for a 0.4 ha grid size, $15 per hectare for a 1.0 ha grid size, and $10 per hectare for the remaining larger grid sizes of 2.0 to 4.0 ha. A soil analysis cost of $6 per sample was used which again represented the nominal soil sample analysis fees charged by most private and public soil testing laboratories in the southeastern US. Table 2.2 below illustrates an example of the calculation of total cost ($ ha^{-1}) for different grid sizes for lime application in one of the fields used in this study. The total cost per hectare for each grid size strategy is the sum of the soil sampling cost, analysis cost (which varied based on the grid size and the number of soil samples), and the lime/fertilizer costs (which depended on the total amount of lime/fertilizer prescribed by each grid size strategy). Additionally, the total cost per hectare for fertilizing the field was computed by combining per-hectare costs associated with each nutrient (lime, P, and K).

Table 2.2 Example of computation of total cost ($ ha^{-1}) for lime application based on soil sampling on different grid sizes for one of the fields used in this study.

Grid Size (ha)	Samples	Sampling Cost ($ ha^{-1})	Analysis Cost ($ ha^{-1})	Total Lime Rec. (kg)	Lime Cost ($ ton)	Total Lime Cost ($ ha^{-1})	Total Cost* ($ ha^{-1})
0.4	90	20	14	55,690	50	37	71
1.0	35	15	6	48,050	50	32	53
2.0	17	10	3	43,344	50	29	42
3.0	13	10	2	47,020	50	31	43
4.0	8	10	1	62,164	50	41	52

*Total cost is the sum of the cost of soil sampling, analysis, and lime.

2.4 Results and Discussion

2.4.1 Effectiveness of Different Grid Sizes

The application accuracy results for soil sampling at different grid sizes are presented separately for each nutrient (lime, P, and K) in the following sections. The data presented in Tables 2.3, 2.4, and 2.5 for lime, P, and K, respectively shows the percent of under-application, on-target (accurate), and over-application associated with soil sampling at different grid sizes (0.4, 1.0, 2.0, 3.0 and 4.0 ha) in each field. It is also important to note that the application data presented in these tables was computed by performing comparisons to the reference application map, which was based on the high-density soil sampling (2.5 samples per hectare) and assumed to represent the actual spatial variability within each field. Additionally, as visual representation helps in better illustrating the differences among the maps, the reference prescription map and prescription maps generated using soil sampling at different grid sizes are also presented for lime, P, and K in Figures 2.3, 2.4, and 2.5, respectively for one of the fields (Field 2) used in this study.

2.4.2 Lime Application Accuracy

The 0.4-ha grid size provided the best lime application accuracy (>85%) in most fields while the under- and over-application, on average, increased with grid size (Table 2.3).

This trend of decreased lime application accuracy with increasing grid size was observed in all nine fields and can be attributed to the fact that as grid size increases, the distance between the adjacent sampling points increases which makes the interpolation procedure (IDW in this case) predict across the field with fewer known points. The 1.0-ha grid size resulted in lime applications that were ≥80% accurate in only four fields while the accuracy ranged between 66% and 78% in the rest of the fields. This can be due to the high amount of soil pH variability in these fields, and these data also suggested that the application accuracy in these fields can be considerably lower even from a grid size of 0.4 ha to 1.0 ha.

For grid sizes of 2.0 ha and greater, the lime application accuracy was mostly inconsistent ranging between 19% and 82% among the fields. However, in one of the fields (Field 3), the application accuracy was >85% even at the larger grid sizes of 2.0 and 3.0 ha, likely due to the low soil pH variability within this field (min soil pH=6.0, max soil pH=6.4). While a general trend regarding the on-target (accurate) lime application existed between the fields (Table 2.3), no particular trend in the amount of over- and under-application was observed. In general, the inaccuracy of lime application increased with grid size with the under- or over-application mostly under 20% for grid sizes of 1.0 ha and lower. For grid sizes of 2.0 and greater, the under- or over-application was as large as 50% or more in some fields.

The VR lime prescription maps presented in Figure 2.3 support these findings where the prescription map based on the 0.4 ha grid size (Figure 2.3b) is most closely related to the reference lime prescription map (Figure 2.3a) whereas the association between the prescription maps decreases thereafter for grid sizes of 1.0 ha and greater (Figure 2.3, c -

f). The corresponding under- and over-application associated with each grid can also be noticed by observing the change in the area for each recommended lime application rate.

Table 2.3. Lime application accuracy for soil sampling at different grid sizes. Data represent the percent over-application, on-target, and under-application associated with each grid size for all nine fields used in this study.

Field	Application	0.4	1.0	2.0	3.0	4.0
				(%)		
1	Over	4	1	0	6	5
	Target	95	92	75	94	65
	Under	2	8	25	0	30
2	Over	10	3	1	12	47
	Target	87	66	51	46	45
	Under	3	31	48	42	9
3	Over	2	1	11	2	65
	Target	95	93	87	92	30
	Under	3	6	3	6	2
4	Over	8	13	29	8	4
	Target	90	70	65	70	48
	Under	3	17	6	22	48
5	Over	11	9	13	25	25
	Target	75	82	80	75	75
	Under	14	9	8	0	0
6	Over	7	3	12	2	2
	Target	91	41	68	41	41
	Under	1	56	20	57	57
7	Over	6	9	7	0	4
	Target	90	78	81	89	54
	Under	4	13	13	11	42
8	Over	6	3	9	29	41
	Target	89	85	75	66	34
	Under	5	13	16	5	24
9	Over	5	13	22	8	24
	Target	91	76	77	81	76
	Under	4	9	1	10	0

As an example, Figure 2.3a (reference map) shows that the 18.8 and 17.1 ha within the field would receive the recommended lime application rate of 1,120 and 1,680 kg ha-1, respectively. Now observing the prescription map based on the 0.4 ha grid size (Figure 2.3b), the area within the field receiving the lime application rates of 1,120 and 1,680 kg ha-1 are 16.5 and 19.5 ha respectively, which means that around 2.3 ha in the field will be over-applied based on soil sampling at 0.4-ha grid size. Similarly, the areas within the field for the 1.0 ha grid sizes (Figure 2.3c) receiving the application rates of 1,120 and 1,680 kg ha-1 are 9.0 and 27.2 ha, respectively indicating that 8.4 ha in the field will be under-applied based on soil sampling at 1.0 ha grid size. This under- or over-application of lime further increases with grid size and can be noticed by observing the change in areas within different lime application rates in Figures 2.3d, 2.3e, and 2.3f.

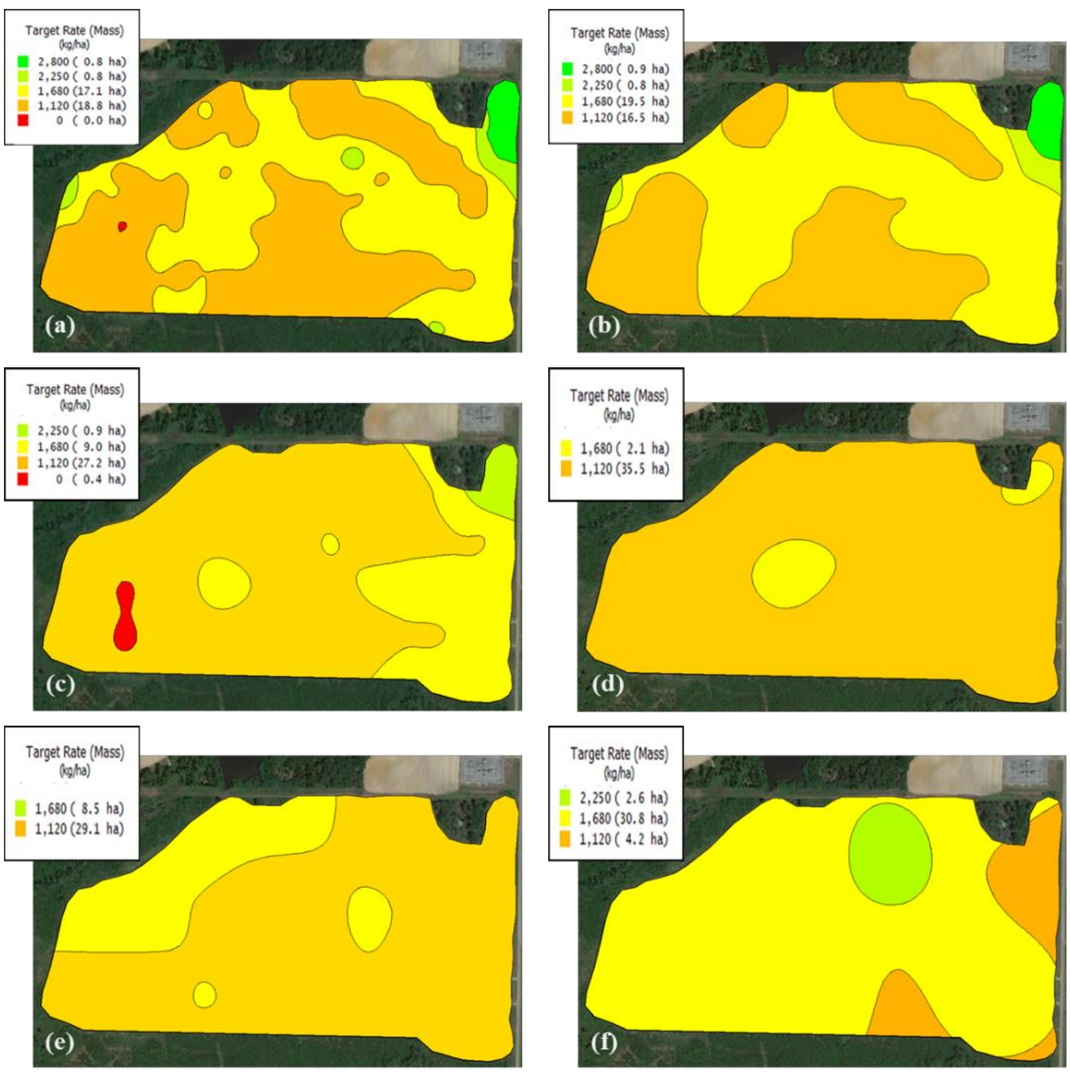

Figure 2.3 (a) depicts the reference lime prescription map based on the high-density soil sampling (2.5 samples per hectare) whereas (b - f) represents the variable-rate lime prescription maps based on soil sampling grid sizes of 0.4 to 4.0 ha, respectively for one of the fields used in this study.

2.4.3 Phosphorus (P) Application Accuracy

As observed in Table 2.4, the application accuracy for P at the 0.4 ha grid size was >80% for most of the fields, except for field 7 where it was below 75%. Similar to the trend observed for the lime application, the application accuracy of P decreased with an increase in grid size. The application accuracy for the 1.0-ha grid size was ≥80% for only three of the nine fields while it ranged between 36% and 68% for all other fields. For the grid sizes of 2.0 to 4.0 ha, the application accuracy varied considerably among the fields and ranged anywhere from 19% up to 82%. These data show the inconsistency in the effectiveness of larger grid sizes, especially greater than 2.0 ha, and their ability to accurately depict P variability across the fields. While there is one field (Field 4) with an on-target application of >80% for the larger sizes of 2.0 and 3.0 ha, this is again likely caused by the low P variability in this field. Similar to the lime application, the amount of under- and over-application for P did not follow a particular trend and increased with grid size. For grid sizes of 1.0 ha and lower, the amount of under-application was ≤30% for all the fields whereas the over-application was <20% except for two fields (Fields 1 and 7).

The prescription maps for P, shown in Figure 2.4 for one of the fields (Field 2), show a general trend observed in the data presented in Table 2.4. The application areas for different P application rates in the prescription map for the 0.4 ha grid size (Figure 2.4b) resemble closely with the application areas in the reference prescription map (Figure 2.4a); however, these similarities among the prescription maps diminish quickly as grid size increases. Observing the prescription maps in Figure 2.4, it can be noticed that while the total area under different P application rates does not vary considerably between the maps, the under- and over-application in the field was still noticeable as the grid size increased. This is due to the difference in the spatial accuracy of P among these maps, which indicates that in some cases the total area within the field receiving a particular application rate may not change between grid sizes, but the spatial accuracy of nutrient application is reduced with an increase in grid size. Therefore, assessing spatial locations of under- and over-applications within each field along with the total amount is also important to accurately understand the effectiveness of different soil sampling strategies.

Table 2.4 Phosphorus application accuracy for soil sampling at different grid sizes. Data represent the percent over-application, on-target, and under-application associated with each grid size for all nine fields used in this study.

Field	Application	0.4	1.0	2.0	3.0	4.0
		-------------------------------(%)------------------------------				
1	Over	5	45	81	50	12
	Target	82	40	19	32	42
	Under	13	16	0	18	47
2	Over	10	12	26	21	22
	Target	84	58	49	42	42
	Under	6	30	26	36	35
3	Over	7	3	33	12	1
	Target	88	82	51	64	37
	Under	5	15	16	24	63
4	Over	6	6	5	6	7
	Target	92	82	81	82	72
	Under	2	13	13	12	21
5	Over	10	20	45	12	4
	Target	81	57	46	55	55
	Under	9	22	10	33	41
6	Over	7	12	22	18	28
	Target	91	60	65	60	64
	Under	2	28	14	23	8
7	Over	1	58	35	54	77
	Target	75	36	53	32	20
	Under	23	5	12	14	3
8	Over	2	12	20	17	7
	Target	92	82	70	74	77
	Under	6	6	10	9	15
9	Over	3	19	27	21	36
	Target	91	68	63	67	57
	Under	6	14	10	12	8

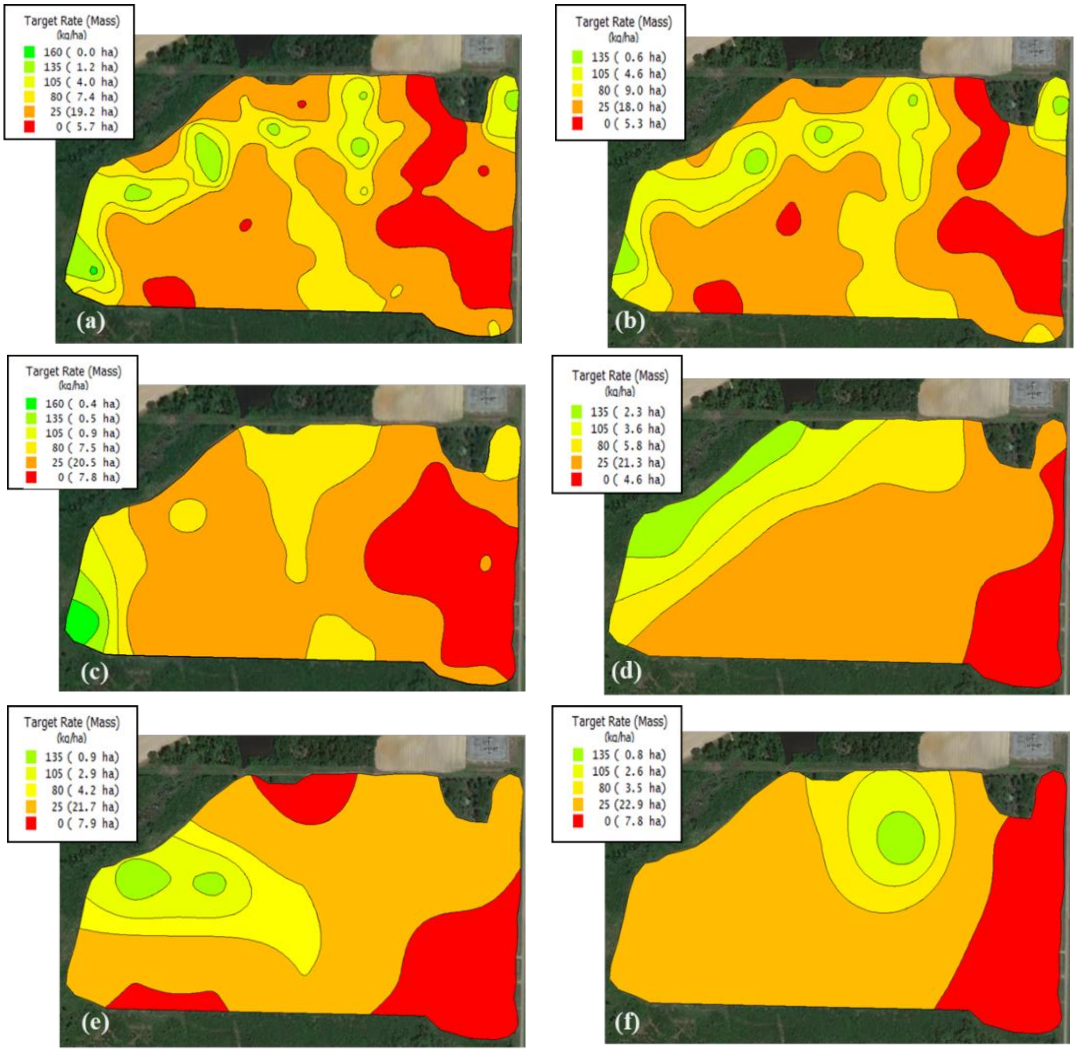

Figure 2.4 (a) depicts the reference phosphorus prescription map based on the high-intensity soil sampling whereas (b - f) represents the variable-rate phosphorus prescription maps based on soil sampling grid sizes of 0.4 to 4.0 ha, respectively.

2.4.4 Potassium (K) Application Accuracy

The application accuracy results for K for the 0.4 ha grid size were similar to both lime and P where it exhibited an application accuracy of ≥84% for all fields except for field 5 where it was 73%. The spatial K variability in field 5 was high ranging from 70 to 338 kg ha^{-1}. These data also suggest that in some fields, spatial nutrient variability can be difficult to capture even with a grid sampling size of 0.4 ha. For the 1.0 ha grid size, none of the fields had K application accuracy above 80% which again indicated that most of these fields had high amounts of K variability which cannot be depicted with soil sampling at grid sizes of 1.0 ha or greater. The application accuracy for larger grid sizes (2.0 - 4.0 ha) for all fields was in the range of 26 to 68% indicating their poor performance compared to the 0.4 ha grid size. The low application accuracy associated with larger grid sizes also suggests that the long-term reliance on these grid sizes to make K prescription maps could be detrimental to the areas of the fields that are receiving an over-application of K year after year. As observed for lime and P, no particular trend in under- and over-application existed for K with grid size. For grid sizes of 1.0 ha and greater, the under-application ranged between 1% and 66% whereas the over-application varied between 2% and 54% across all the fields used in this study.

The prescription maps for K (Figure 2.5) also showed a similar trend as observed for lime and P (Figure 2.3 and 2.4, respectively) where the prescription K map based on the 0.4 ha grid size (Figure 2.5b) is comparable to the reference K map (Figure 2.5a). However, this association between the reference map and other prescription maps (Figure 2.5, c -f) decreases rapidly as the grid size increases. Referring to the prescription maps in Figures 2.5a and 2.5b, the areas within the field receiving different target K application rates are very similar with only about 1.0 ha of the field being over-applied. The areas receiving the same K application rates in Figure 2.5 (c - f) vary considerably from the reference K map indicating a high under- and over-application associated with grid sizes of 1.0 ha and greater. Unlike P maps (Figure 2.4) where the total area within each P application rate stayed somewhat similar, the maps for K highlight the differences in both the magnitude and spatial resolution of application accuracy associated with soil sampling at different grid sizes.

Table 2.5 Potassium application accuracy for soil sampling at different grid sizes. Data represent the percent over-application, on-target, and under-application associated with each grid size for all nine fields used in this study.

Field	Application	0.4	1.0	2.0	3.0	4.0
				(%)		
1	Over	7	20	1	16	23
	Target	86	64	59	63	53
	Under	8	16	40	20	23
2	Over	9	20	16	7	32
	Target	85	57	52	49	44
	Under	6	22	32	45	24
3	Over	6	12	27	24	31
	Target	84	61	48	45	60
	Under	10	26	25	31	9
4	Over	4	26	24	25	16
	Target	84	64	61	57	54
	Under	12	10	15	18	30
5	Over	19	20	23	19	21
	Target	73	42	30	27	26
	Under	8	38	47	54	53
6	Over	8	32	32	33	19
	Target	84	57	55	54	64
	Under	8	12	12	14	16
7	Over	1	35	19	51	66
	Target	89	59	68	38	32
	Under	10	6	13	11	2
8	Over	5	13	10	30	28
	Target	88	72	66	49	54
	Under	6	14	23	21	18
9	Over	11	27	32	25	15
	Target	87	61	39	51	58
	Under	2	12	29	24	27

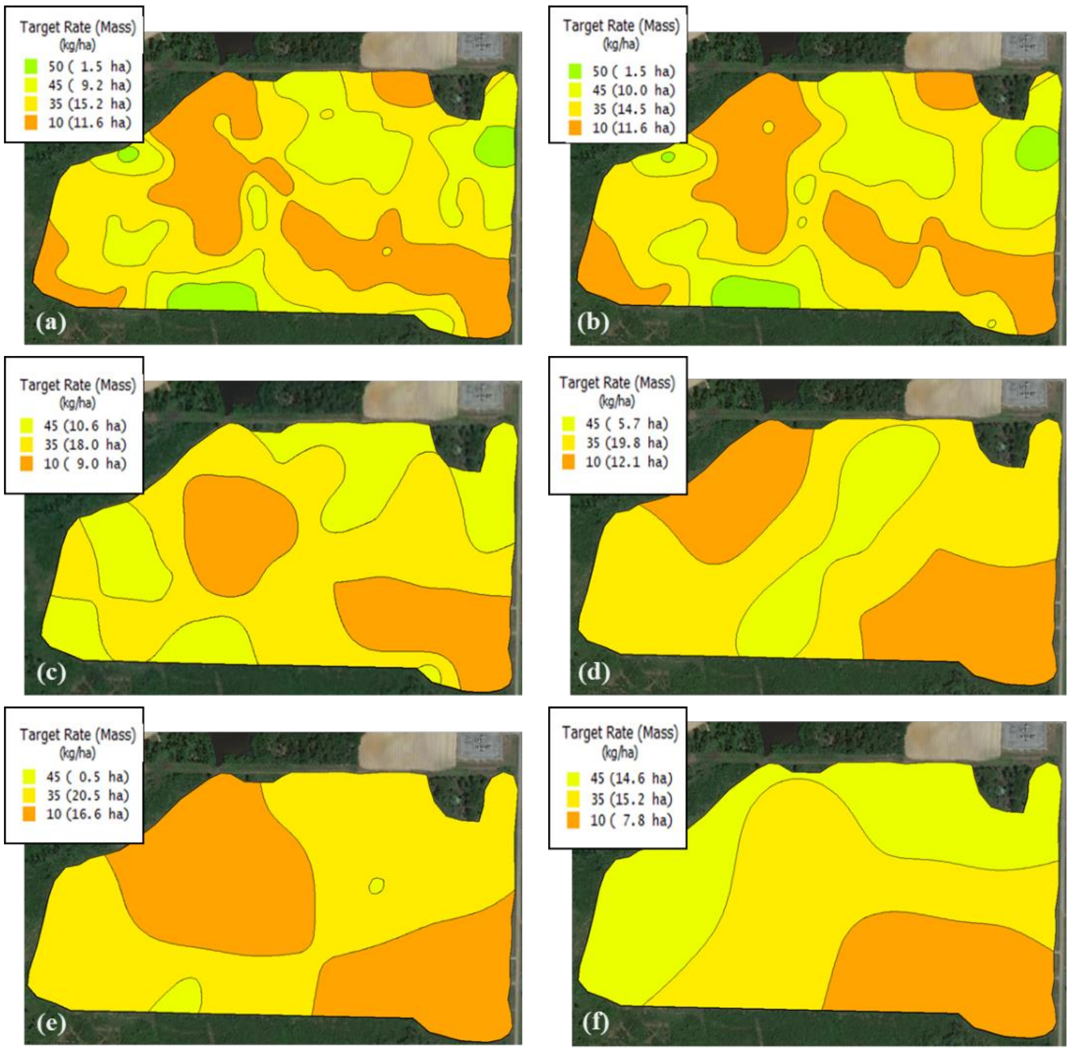

Figure 2.5 (a) depicts the reference potassium prescription map based on the high-intensity soil sampling whereas (b - f) represents the variable-rate potassium prescription maps based on soil sampling grid sizes of 0.4 to 4.0 ha, respectively.

Observing the data altogether for all three nutrients in Tables 2.3 to 2.5 also highlights an issue that may arise for a grower when choosing a grid size for their farm due to the variation in the accuracy among different nutrients. For example, a grower may choose to collect samples using a 2.0 ha grid for field 7 which exhibited an on-target lime application of >80% but it was only 53% and 68%, respectively for P and K at the same grid size. Similar observations can be made for other fields as well where a certain grid size provided a high application accuracy for one nutrient but may not be suitable for other nutrients.

These results indicate that the selection of an optimal grid size could be different for each field and each nutrient; however, it is not feasible for a grower to collect soil samples at different grid sizes in the same field to target different nutrients. For this reason, it may be optimal to determine the best soil sampling grid size for each field individually; however, as farms grow larger, the need to be efficient with different operations is increased, including soil sampling. While conducting soil sampling on different grid sizes across the farm may be feasible for a few growers, it is not practical for most growers in the southeastern US.

Table 2.6 presents the application accuracy averaged across all nine fields for lime, P, and K along with CV values that represent the amount of variability that existed among the fields for each nutrient. When averaged across all fields, the overall results again exhibit a similar trend for all three nutrients in that the application accuracy is highest from 84% to 89% at a grid size of 0.4 ha whereas it decreased considerably for grid sizes of 1.0 ha and greater to below 73% for lime, and to below 63% and 60% for P and K, respectively. As indicated by the low CV values (6 – 7%), the results for 0.4-ha grid size were also consistent across all the fields while the relatively higher CV values for grid sizes of ≥1.0 ha indicate that the application accuracy depicted using larger grid sizes can vary among the fields depending on the nutrient variability within the field and previous management history. The results obtained in the present study for application accuracy of lime, P, and K at different soil sampling grid sizes are similar to the observations shared by previous studies. Wollenhaupt and Wolkowski (1994) recommended that a 0.4-ha grid sampling method is the most appropriate in the first year to determine the amount of nutrient variability within the field. After the first year, the authors speculate a thorough nutrient budget, maintaining accounts of fertilizer applications and crop removals, will be sufficient to make fertilizer applications in the following years. Additional samples can be collected in the following years if no significant response to fertilizer application is found. Stępień et al. (2013) chose 1.0 ha to be their densest sampling but suggested that there could be more variability present within the fields for some nutrients, that were not captured by the 1-ha grid size. The authors recommend a sampling size of 1.0 ha, with the option to collect samples on a coarser grid size (2.0- or 4.0- ha) for the two years following. Mallarino and Wittry (2004) found that a 1.2 to 1.6 ha grid sampling method had an accuracy of 54% and 66% for P and K, respectively. These findings were similar to the accuracy values attained in the present study where a 1.0-ha grid size exhibited an application accuracy of 63% and 60% for P and K, respectively. It is evident that a grid size of 0.40 ha captures the greatest nutrient spatial variability within the fields and results in the highest application accuracy than other larger grid sampling sizes.

Table 2.6. Application accuracy of lime, phosphorus, and potassium for different grid sizes. Data is averaged across all fields.

Grid Size	Lime		Phosphorus		Potassium	
	Target (%)	CV (%)	Target (%)	CV (%)	Target (%)	CV (%)
0.4	89	7	86	7	84	6
1.0	69	38	63	28	60	14
2.0	73	15	55	32	53	24
3.0	64	42	56	32	48	22
4.0	52	32	52	35	49	26

2.4.5 Economics of Different Grid Sizes - Material Costs

Besides assessing application accuracy, it is important to evaluate the economics of different soil sampling grid sizes to identify an optimal soil sampling that is also cost-effective. Tables 2.7 through 2.9 present the material cost per hectare for lime, P, and K applications, respectively, based on different soil sampling grid sizes in each field. The data presented in these tables illustrates how total material cost (computed from the amount of material recommended by each grid size strategy) changes with application accuracy. For this calculation, the cost of soil sampling and lab analysis is excluded as they are included in the total cost in the following section. It should be noted that because the material cost is directly related to the amount of over- and under-application associated with each grid size, the trend observed for lime and fertilizer costs was mostly similar to the application accuracy discussed in the previous sections. This can also be explained as that the costs were higher where the lime or fertilizer was over-applied, and they were lower where the lime or fertilizer was under-applied. For instance, Field 2 in Table 2.7 reports the cost of lime as 81, 70, 63, 69, and 91 dollars per hectare for grid sizes of 0.4, 1.0, 2.0, 3.0, and 4.0 ha, respectively. There is a decrease in the cost of lime per hectare for the 1.0, 2.0, and 3.0 ha grid sizes and an increased cost of lime per hectare for the 4.0 ha grid size. Now observing the application accuracy for different grid sizes for the same field in Table 2.3, data shows an increase in under-application of lime for the 1.0, 2.0, and 3.0 ha grid sizes and an increase in over-application of lime for the 4.0-ha grid size when compared to the 0.4 ha grid size. Although the smallest grid size of 0.4 ha recommends more lime per hectare (higher cost per hectare) when compared to the larger grid sizes, the application accuracy at this smaller grid size is also high (87%) for this particular field as opposed to <66% for the larger grid sizes. A practical implication of these results, in this case, would be that in some fields, a grower would have a higher application cost due to greater fertilizer cost, but they will also be more confident in the accuracy of site-specific fertilizer application (placement) by selecting a grid size of 0.4 ha. There is also an expectation that yields will be increased due to the correct placement of nutrients, increasing profit margins.

As discussed in the previous example, precision fertilizer application through soil sampling on a smaller grid size doesn't necessarily always correlate to high application costs but can also help in reducing the total application costs in some cases. This can be noticed, for example, in Table 2.8. For Fields 7, 8, and 9, the 0.4-ha grid size recommends the lowest material (lime and fertilizer) cost per hectare when compared to the 1.0, 2.0, 3.0, and 4.0 ha grid sizes. In this case, it can be attributed that 0.4-ha grid size has the highest application accuracy which means low under- and over-application (Table 2.4). It can again be noticed in these fields where the application accuracy decreases (increase in over- or under-application), and the cost of material follows the same trend as the amount of over and under-application. If there is greater over-application then the total cost of material will also increase and if there is under-application then the total cost of material will decrease.

Similar observations are seen throughout the other fields and nutrients in the present study and are ultimately the reason that there is no general trend with the data displayed in Tables 2.7-2.9, as the total cost per hectare of material depends primarily on the amount of over- and under- application that occurs in each field, which is presented in Tables 2.3-2.5.

Table 2.7 Total material cost per hectare of lime for different soil sampling grid sizes.

	0.4	1.0	2.0	3.0	4.0
Field	-------------------------		($ ha^{-1})		-------------------------
1	59	55	45	62	44
2	81	70	63	69	91
3	60	58	66	62	84
4	69	68	77	66	43
5	84	85	88	92	92
6	74	62	73	62	62
7	57	51	52	0	33
8	26	19	24	37	31
9	114	142	122	114	123

Table 2.8 Total material cost per hectare of phosphorus for different soil sampling grid sizes.

	0.4	1.0	2.0	3.0	4.0
Field	-------------------------		($ ha^{-1})		-------------------------
1	93	123	182	136	78
2	67	51	65	48	46
3	35	31	44	22	5
4	13	7	8	7	2
5	173	167	188	166	157
6	46	33	58	51	67
7	42	100	77	96	127
8	16	22	19	22	14
9	87	93	107	102	113

Table 2.9 Total material cost per hectare of potassium for different soil sampling grid sizes.

	0.4	1.0	2.0	3.0	4.0
Field	-------------------------		($ ha^{-1})		-------------------------
1	93	98	42	85	94
2	114	119	105	90	125
3	152	152	160	155	168
4	30	42	47	39	27
5	139	128	122	97	108
6	56	61	60	59	42
7	16	32	22	42	55
8	196	195	191	200	200
9	189	194	194	190	184

2.4.6 Economics of Different Grid Sizes – Application Costs

Table 2.10 presents the total application cost per hectare based on different grid sizes for all the fields. The total application cost per hectare includes the cost per hectare of each material (lime, P, and K), the cost per hectare for the collection of the soil samples, and the cost per hectare for the analysis of the soil samples. When observing the data in Table 2.10, it is difficult to define a particular trend or trends across the fields and also between the different grid sizes because many factors can influence the total application cost per hectare. These factors are, but are not limited to, the application accuracy associated with each grid, the cost of fertilizer, and the cost of the soil sampling method.

For most fields, the 0.4-ha grid sampling method does result in the highest cost per hectare, which is expected due to the higher cost of sampling and analysis associated with the smaller grid size. Interestingly, on average, the change in total application cost per hectare from a 1.0-ha to a 0.4-ha sampling grid represents an increase of less than 2.5% of the total cost per hectare. However, this change in soil sampling grid size will, on average, also increase the application accuracy by >20% for lime, P and K. While changing soil sampling from a 2.0-ha grid size to a 0.4-ha grid size will cost on average 3% more per hectare in sampling costs, lab analysis, and material, the application accuracy increase is >30% for P and K. Understanding that producers may not be willing to make such a large shift to 0.4-ha grids, going from a 2.0-ha grid size to a 1.0-ha grids increases the total cost by 1.6% and an increase in application accuracy of 4% on average.

Table 2.10. Total application cost per hectare for soil sampling on different grid sizes.

Field	0.4	1.0	2.0	3.0	4.0
	--------------------------($/ha)--------------------------				
1	279	297	282	295	226
2	296	261	246	219	273
3	282	263	283	251	268
4	146	137	145	124	84
5	429	401	410	367	369
6	210	176	203	183	181
7	149	204	165	151	225
8	271	257	247	272	256
9	424	450	436	418	431

Overall, when considering both the application accuracy and total application costs associated with different soil sampling grid sizes, the results obtained in this study are helpful to producers in the southeastern U.S. as they highlight the strengths and weaknesses of different soil sampling grid sizes as well as the importance of selecting a proper grid size as it can greatly influence both accuracy and costs. If the 9 fields used in this study were to represent a sub-sample of a growers' farm, the data suggests an optimal grid size would vary from a field-by-field basis. However, when considering the overall results across all the fields, it is also evident that the 0.4 ha grid size does perform better than all other grid sizes but it may come at the expense of increased cost in some fields. However, it can also be said that some growers are more willing to spend money in areas or fields with high-yield potential. Considering that, precision soil sampling on a smaller grid size such as 0.4 ha gives those producers a higher confidence in their nutrient management by ensuring fertilizer application at the correct rate and the correct place. It is important to emphasize here that the most common grid size currently used for precision soil sampling across the southeastern US is 2.0 ha, which only exhibited 50% to 70% application accuracy across nine fields in this study. Interestingly, the larger grid sizes of 3.0 and 4.0

ha are also used by some consultants and growers in the southeastern US, the results attained here suggest an incredibly large amount of under- or over-application of nutrients associated with them. While lowering soil sampling costs is one of the main reasons behind larger grid sizes, the authors believe that this effort to save is costing growers more in fertilizer application inaccuracies and consequently in crop yields. In some cases, these inaccurate fertilizer applications could also cause more nutrient variability than originally present in the field. Therefore, growers who have soil sampled on larger grid sizes over the years need to be cautious about inadvertently causing these nutrient variations in their fields. Based on the findings in this study, it is recommended that most fields should be soil sampled on a 0.4 ha grid size at least once to understand the nutrient variability within each field and to make a decision for subsequent years if it needs to be soil sampling on 0.4 ha or larger grid size. While most fields have some sort of inherent variability due to soil type, texture, or management, the authors do believe that some (mostly uniform) fields can be soil sampled on larger grid sizes to manage soil sampling costs. This also presents a relatively different approach to soil sampling as currently the soil sampling is performed on one grid size across the whole farm; however, there could be an opportunity for growers to be more efficient with nutrient management and costs by adopting varied grid sizes for fields across their farm. Though grid soil sampling will remain a prevalent soil sampling practice in the southeastern US, we can expect the adoption of zone-based soil sampling strategies in the future as the interest in precision nutrient management and maximizing yield increases among the growers.

2.5 Conclusions

Site-specific nutrient management through variable-rate application of lime and fertilizer is one of the most widely adopted practices in the US including in the southeastern region. The rising fertilizer costs and increased interest among growers in precision nutrient management have recently raised concerns and questions about the efficacy of different grid sizes nominally used for precision soil sampling across the southeastern US. Thus, this study was aimed at evaluating the effectiveness of different soil sampling grid sizes (0.4, 1.0, 2.0, 3.0, and 4.0 ha) in depicting the spatial nutrient (soil pH, P, and K) variability within nine agricultural fields and their influence on the accuracy of variable-rate fertilizer prescription maps. Results from this study showed that the smallest grid size of 0.4 ha was the best at representing the most spatial variability for soil pH, P, and K within the selected fields while the ability to depict spatial variability decreased significantly with an increase in grid size. The resulting VR prescription maps generated from soil sampling at different grid sizes indicated a similar trend where the potential for under- or over-application was the least for the smaller grid sizes and the highest for the larger grid sizes. In general, it was noticed across all nutrients that the application accuracy was greatest for grid sizes of 0.4 ha (>80%) while it varied considerably (20% to 90%) among the fields for grid sizes equal to or larger than 1.0 ha. Lower CV values (6 – 7%) for application accuracy of lime, P, and K also indicated that the findings for 1.0 ha grid size were also consistent among all nine fields.

Over the years, one of the major drivers behind the push towards larger soil sampling grid sizes has been the increased costs of soil sampling; however, that approach fails to consider the effect of larger grid sizes on the fertilizer costs per hectare. Thus, this study also investigated the economics of soil sampling on different grid sizes, including considering the soil sampling costs, sample analysis costs, and material (lime, P, and K) costs, to better understand if there is a certain trend to the total application costs with the increase in soil sampling grid size. Results from the economic analysis suggested that while the soil sampling costs are mostly fixed (independent of the grid size) and soil analysis costs are directly proportional to the grid size – the smaller the grid size, the greater the number of samples; the fertilizer costs were correlated to the amount of under- and over-application associated with different grid sizes within each field. This also influenced the total application costs as a high amount of under-application resulted in low material costs and vice-versa. Overall, these data suggested that while the larger grid sizes, especially ≥2.0 ha, may help in lowering soil sampling costs, the total application costs including fertilizer costs can be lower or higher than the total costs for soil sampling on smaller grid sizes (0.4 or 1.0 ha), depending on the amount of under- and over-application. Direct impacts of accurate nutrient inputs are beyond the scope of this study, but, likely, higher nutrient use efficiency would also translate to better yield. In some cases, the 0.4-ha grid size may have the highest application costs than other grid sizes but it also ensures the greatest application accuracy. Similarly, in some fields, the total application costs associated with larger grid sizes could be lower than the 0.4-ha grid size but not without the added expense of significant under-application of nutrients in certain areas of those fields. In conclusion, the smaller grid sizes of 0.4 or 1.0 ha are most optimal when considering both the accuracy of VR fertilizer applications and the total application costs.

CHAPTER 3

EVALUATION AND COMPARISON OF DIFFERENT ZONE-BASED SOIL SAMPLING METHODS FOR SITE-SPECIFIC NUTRIENT MANAGEMENT[2]

[2] Tucker, M., Virk, S., Harris, G., Levi, M., Lessl, J. To be submitted to a peer-reviewed journal.

3.1 Abstract

Precision soil sampling strategies are commonly used to determine areas in the field for site-specific application of soil amendments and nutrients. Grid-based soil sampling is a predominant practice in the southeastern US and research has shown that the nutrient application accuracy decreases significantly for grid sizes greater than 1.0 ha. Precision soil sampling on grids, especially on 0.4 and 1.0 ha, incurs considerable soil sampling and analysis costs. Thus, there has been an increased interest among consultants and growers recently in understanding the potential of zone-based soil sampling methods to lower some of the soil sampling costs while maintaining high application accuracy. Currently, many precision ag companies offer zone-based soil sampling services that combine homogeneous areas of the field and present information on zones for soil sampling. To better understand the potential of different zone-based soil sampling methods for site-specific soil nutrient management, a study was conducted in six fields in southern Georgia using three different zone-based soil sampling methods. Soil samples were also collected on 0.2-ha grids to determine and use that information as a reference for comparison among the zone strategies. The first strategy utilized soil electrical conductivity (EC) to create management zones while the second approach utilized a gamma radiation sensor to detect variability in the soil and create management zones for soil sampling based on the company's algorithm. The third strategy utilized the gamma radiation sensor but used the raw data to delineate management zones. The soil sampling based on each of the three strategies was conducted in Spring 2023 and all the soil test results of each method were analyzed. Variable-rate nutrient application maps (lime, P, and K) based on each strategy were created and compared to the reference map generated from the 0.5 ac grid sampling

method. Zone-based sampling methods did decrease the amount of soil samples in each field, but the consistency of the application accuracy was also decreased. Promising results were found that the zone delineation methods could be successful, but further research is needed to determine the best way to collect samples within the zones to make sure a representative nutrient value is assigned for each zone. Collecting soil samples with a grid size smaller than 1.0 ha should be preferred to best understand the nutrient variability in the fields, until zone-based management zone strategies can be studied further.

3.2 Introduction

Proper nutrient management in row crops is crucial for producing high-yielding and high-quality crops. Most agricultural production fields in the southeastern U.S. have high amounts of spatial variability regarding soil physical properties and nutrient levels, due to variations in climate, landscape, and management (Duffera et al., 2007). Single-rate broadcast applications can cause variations in nutrient levels causing areas of yield loss that can take years to improve (Sawyer, 1994). Precision agriculture techniques allow fields to be divided into smaller homogenous areas that can be managed separately from the adjacent areas. Variable-rate application of soil amendments and fertility have proven to be cost-effective and increase yields to the area's potential when conducted appropriately. Variable-rate technology achieves the right place and right rate of the 4Rs of nutrient management (IPNI, 2012). Soil sampling is an important component of site-specific nutrient management in precision agriculture. Precision soil sampling techniques such as grid- or zone-based sampling methods are utilized to determine spatial variability of soil pH and nutrients within fields and are commonly used for variable-rate fertilizer applications (Ackerson, 2018).

Various methods are used by growers use to collect soil samples to determine spatial nutrient variability and inform variable-rate applications, with grid-based approach (1.0- and 2.0-ha grids) being the most common in the southeastern US. Wollenhaupt (1994) found that grids should be no larger than 0.40 ha to capture the spatial nutrient variability. The author also found that grid-based sampling produced maps with higher accuracy when compared to zone-based sampling. Different management zone (MZ) based strategies have also been investigated by researchers in the past including using farmer experience and aerial imagery (Fleming et al., 2004), stable yield maps from multi-year yield data (Flowers et al., 2005), topography (Kravchenko et al., 2000), and electrical conductivity (EC) (Johnson et al., 2003). Farmer experience and soil color maps created from aerial imagery identified homogeneous sub-regions within fields, but the effectiveness varied across different fields (Fleming et al., 2004). Flowers et al. (2005) found multi-year yield maps to be nearly as effective at delineating soil nutrient variability as 1.0-ha grids. Johnson et al. (2005) investigated the use of soil EC and found that there was no consistent relationship between EC and yield variability. However, the addition of other data layers could be used to establish MZs that correlate to crop yield.

The adoption and utilization of these strategies vary considerably among growers, especially in the southeastern United States (Mooney et al., 2010). With grid-based soil sampling being labor intensive and costly (due to the large number of grids used to determine nutrient spatial variability), there is a growing interest among growers in adopting zone-based soil sampling strategies, but the proper selection of management zone differs among the users depending on several factors. Hence, questions from growers and consultants regarding the suitability of different zone-based soil sampling approaches and the type of information needed to delineate management zones for soil sampling are common. Therefore, the objective of this study was to evaluate and compare different zone-based soil sampling methods with the goal of a better understanding of how zone-based soil sampling strategies influence the depiction of soil nutrient variability and site-specific nutrient application requirements within fields.

3.3 Materials and Methods

Data for this on-farm study was collected in 2023 across six different grower fields to be planted in row crops prevalent in the southeastern US (cotton, corn, or peanuts). The selected fields ranged from 9.2 to 37.6 ha in size. All fields were located in the Coastal Plain physiographic region of the southeastern US and had two or more soil types. Detailed information on the location, size, and soil types present within each field is presented in Table 3.1 (Web Soil Survey, 2021). These fields were randomly selected by local county Extension agents with the only criterion that the field be representative of the local geographic area. The soil sampling methods and other procedures were kept consistent among all locations used in this study.

Table 3.1. Location and size of all six fields used in this precision soil sampling study conducted in 2023.

Field	Latitude	Longitude	Size (ha)	Soil Type(s)
1	31.307355	-83.914703	37.6	Tifton, Carnegie, Leefield, Borrow
2	33.209401	-82.503499	36.9	Faceville, Tifton, Orangeburg, Nankin
3	31.729895	-84.463742	25.5	Greenville, Grady
4	31.473537	-83.407591	22.4	Ocilla, Clarendon, Alapaha, Tifton
5	31.351563	-83.930176	9.2	Pelham, Tifton
6	31.351420	-83.926449	10.0	Tifton, Pelham

3.3.1 Grid Soil Sampling

Field boundaries for all fields were imported into a farm data management software (SMS Advanced, AgLeader Technology, Ames, IA), and soil sampling maps were created to effectively have a grid size of 0.2 ha (0.5 ac), as shown in Figure 3.1 for one of the fields (Field 1) used in this study. Two 0.4-ha grid point maps were created and combined in an offset pattern to create the map shown in Figure 3.1. The reason for using two 0.4-ha grids offset from each other was the previous year's sampling in these fields was conducted on 0.4 ha grid and this data was to be used in a separate long-term study to determine the change in nutrient values from year to year when collecting samples in the same location. Sampling this way also allowed for this project to have a 0.2-ha grid sampling method (using all points) and a 0.4-ha grid sampling method (using only half the points). Sampling points were placed at the center of each grid for ease of navigation to the center of the grids during soil sampling. The soil sampling maps were uploaded on a handheld Trimble GPS unit, with a horizontal accuracy of 2-4 m, (Nomad 1050, Trimble Inc., Sunnyvale, CA), which was used to navigate to different soil sampling grids within each field.

In all fields, soil samples were collected using the point sampling method which involved collecting 12 to 15, 15.2 cm deep cores in a 6.1 – 9.1 m radius around each point, and then combining the cores to make a composite sample which represented that grid. All soil samples from each field were placed in a pre-labeled paper bag with the field and sample number. Once all the samples were collected, they were sent to the University of Georgia's Agricultural and Environmental Services Laboratories (AESL) in Athens, GA for soil nutrient analysis. The AESL used Mehlich 1 extractions to determine soil nutrient levels and provided the analysis for soil pH, Phosphorus (P), Potassium (K), Calcium (Ca), Magnesium (Mg), Zinc (Zn), Manganese (Mn), and cation exchange capacity (CEC) for each sample in a .csv format. Since this study only focused on soil pH, P, and K, soil test results for only those nutrients were used for further mapping and analysis.

Figure 3.1 Grid soil sampling map (0.2 ha grids) to illustrate the layout of grids in one of the fields used in this study.

3.3.2 Zone Soil Sampling

Management zones are created to divide the field into sections with similar characteristics. Numerous characteristics that could be used to delineate management zones. Many of them are outdated, labor-intensive, or difficult to collect. For example, soil type is a known soil characteristic that plays into nutrient management, but many NRCS soil survey maps are over 50 years old. Therefore, unless we have extensive knowledge of the field(s) of interest and time to map them to accurately decipher the soil type, this could be an extremely difficult task. Currently, there are few sensing technologies being utilized for mapping large fields to depict different soil properties. Consequently, two different sensors were used in this study to collect data to delineate MZs in all the fields.

3.3.3 Electrical Conductivity

Soil Electrical conductivity (EC) data was collected for the selected fields using a Veris Technologies MSP3 Sensor (Veris Technologies, Salina, KS) pulled using a UTV, as shown in Figure 3.2. The UTV was equipped with a John Deere Starfire GPS/GNSS system with an accuracy of +/- 15 cm. In each field, data was collected by making consecutive passes every 12 m apart and two passes around the field boundary. The data from each field was sent to Veris for post-processing and returned for analysis.

Figure 3.2 Veris Soil EC mapper used for EC data collection in this study.

The EC sensor collects one data point every second (1 Hz) as it is being pulled across the field. A point map was returned from Veris after post-processing (Figure 3.3). This point map was then interpolated using IDW to create a continuous map of the field (Figure 3.4). During the interpolation process, a 9.14 x 9.14 m cell raster map was created for each field. This data was then subjected to a k-means clustering algorithm to determine the appropriate number of zones for each field and section the fields into zones. Soil samples, using the same collection method as the grid sampling, were randomly collected within the zones. All the cores collected inside each zone were mixed and sent to the lab for analysis. By using this method, one composite sample represented a zone, and the entire zone would be assigned the soil property values from this sample.

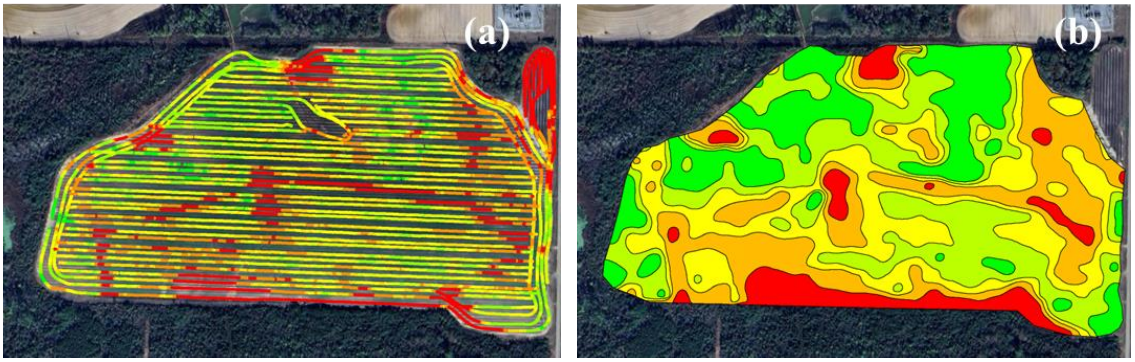

Figure 3.3 (a) Soil EC data before post-processing and (b) soil EC map after interpolation for one of the fields in this study.

3.3.4 Gamma Radiation

The other sensor used in this study was a gamma radiation sensor from Soil Optix, as shown in Figure 3.4. The process for collecting data with this sensor was the same as data collection with the Veris. However, the data and readings among the two sensors are quite different. This sensor measures natural geological properties emitted from the soil; Caesium-137, Uranium-238, Thorium-232, and Potassium-40. This sensor also collects a data point every second (1 Hz) as it travels across the field. This data was submitted to Soil Optix for post-processing where their algorithm correlated the values from the sensor to soil texture and nutrient levels.

Figure 3.4 Soil Optix Gamma Radiation sensor

The data collected from this sensor was used in two different ways in this study. The first method involved data collected by the Soil Optix sensor after being processed by their algorithm and converting it into a raster map for further analysis. The process for collecting soil samples with Soil Optix after the full field has been surveyed is based on a map generated on the field computer. The Soil Optix software generates sampling locations to collect soil samples within the fields as shown in Figure 3.5.

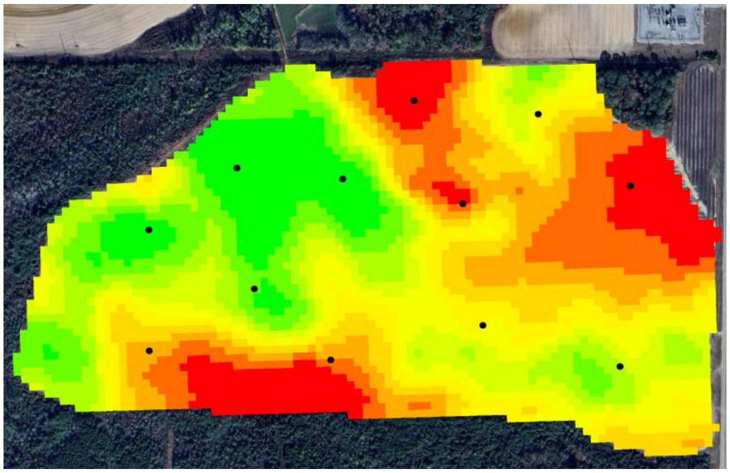

Figure 3.5 Map representing sampling locations recommended by Soil Optix software for one of the fields in this study. Black dots represent soil sampling points recommended by the software.

The Soil Optix software generates these locations based on where the gamma radiation levels were low, medium, and high. The recommended sampling density from the manufacturer for this method is 1 sample per 3 ha. These samples were collected by navigating to the sample location with the sensor on and collecting the samples 2 to 5 m away from the sensor in a semi-circle. These soil samples were labeled according to the Soil Optix software and sent to the lab for analysis. Upon receiving the soil analysis, the data was sent to Soil Optix to validate their algorithm.

The second method to create zones with this data was to process and use the raw data collected from the sensor in the same way as soil EC data. Raw data from the Soil Optix sensor (Count Rate) was interpolated using the IDW method and then ran through a k-means clustering algorithm to determine the appropriate number of zones and sort each raster cell into the zone it belonged to, as shown in Figure 3.6.

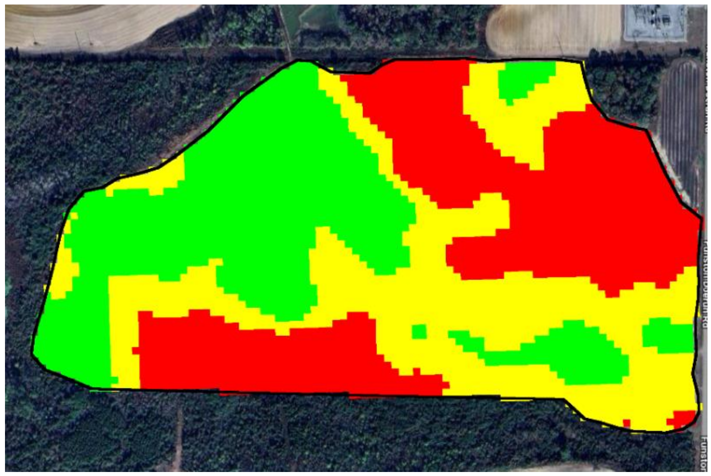

Figure 3.6 Map representing management zones created using Soil Optix Countrate data.

Soil samples were then randomly collected within each zone, and the samples within each zone were combined into a composite sample and submitted to the lab for analysis. When the data was returned, each zone was assigned the soil nutrient values for the entire zone.

3.3.5 Spatial Nutrient Mapping and Analysis

Soil nutrient analysis results for each field were imported into AgLeader SMS Advanced software and used for further spatial analysis and interpolation. For all fields, spatial maps for soil pH, P, and K were created from soil nutrient levels for each soil sampling strategy (both grid and zone) using an inverse distance weighting (IDW) interpolation method. The IDW interpolation uses an algorithm to predict values of unmeasured locations by weighting measured values based on the spatial distance from the unmeasured locations (Burrough et al., 2015). The interpolation process consisted of creating a 9.14 x 9.14 m raster map for each grid size. Each cell in the map was georeferenced and contained soil nutrient values for soil pH, P, and K. The soil analysis results for the 0.2-ha grid were assumed to represent the actual spatial variability within each field and were used as a reference layer for comparison among other maps based on different sampling strategies. This 0.2-ha grid map is hereafter referred to as the reference map for each nutrient. The zone maps for EC and Soil Optix Countrate were created by using a k-means algorithm to determine the appropriate number of zones and how the data would be split into the zones. The raster maps with the interpolated values of soil EC and Gamma radiation (Soil Optix Countrate) were then converted into zone maps by assigning a zone number to each cell of the raster. These zone maps were then imported into a handheld GPS unit and soil samples were randomly collected within each zone. At least 20 cores were collected from each zone and then mixed to send a composite sample (representing each zone) to the lab for analysis.

The variable-rate (VR) lime, phosphorus (P), and potassium (K) prescription maps were created for each zone-based soil sampling strategy for fertilizing cotton for a yield goal of 1345 kg ha^{-1} using the UGA cotton fertilization recommendations (Plank and Harris, 2022). All VR fertilizer prescription maps were converted to raster format to enable direct comparison to the reference prescription map for each nutrient. A comparison between the prescription map for each zone-based strategy and the reference prescription map (based on 0.2-ha grid size) was performed to create a difference map that depicted the spatial location as well as the amount of on-target, under-, and over-application that occurred in different areas within the field, as shown in Figure 3.7. Difference maps were created for all soil sampling methods used in this project: 0.4-ha grid sampling, management zones based on soil EC, management zones created from Soil Optix using their algorithm, and management zones created from raw data from Soil Optix (Countrate). The difference maps used a buffer to allow minor differences in nutrient recommendations to be considered on target, these buffers are as follows: lime +/- 225 kg, P and K +/- 25 kg. These buffers were used because of known dry-spreading equipment restraints and accuracies. These methods are hereafter referred to as 0.4-ha Grids, Soil EC, Soil Optix, and Soil Optix Countrate.

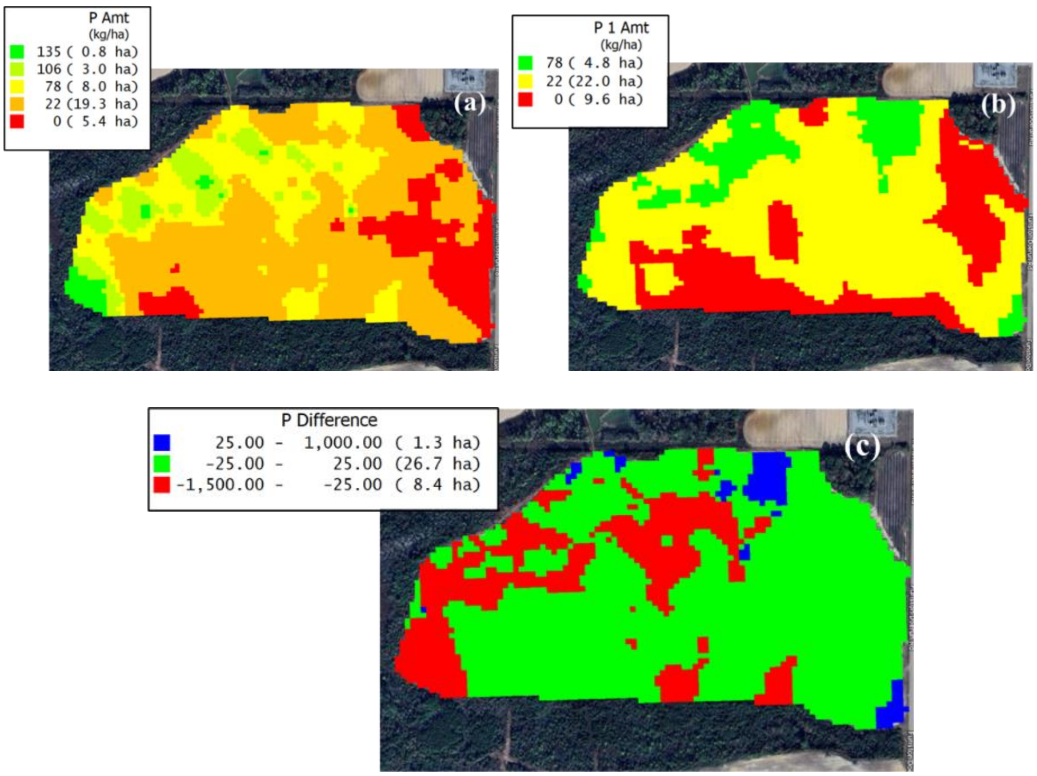

Figure 3.7 Illustration of a (a) prescription map for P based on reference nutrient variability, (b) prescription map generated from EC management zone method, and (c) difference map. In (c), the areas in green represent a portion of the field that received accurate/on-target fertilizer application whereas the areas in red and blue represent under and over-fertilized areas, respectively.

Various soil sampling strategies used in this study required varying amounts of soil samples to be collected from the fields. Zone-based strategies typically call for fewer soil samples to be collected, but have other data collected to help justify the small number of samples. Table 3.2 presents information on the number of soil samples collected within each field for different soil sampling strategies used in this study.

Table 3.2. Information on the number of soil samples collected based on different soil sampling strategies used in this study.

Field	0.4 ha Grids	Soil EC	Soil Optix	Optix Countrate
1	88	3	12	3
2	88	3	12	3
3	64	3	10	3
4	53	3	8	3
5	20	3	4	3
6	24	3	4	3

3.4 Results and Discussion

3.4.1 Effectiveness of Management Zone Sampling

The application accuracy results for each soil sampling strategy are presented separately for each nutrient (lime, P, and K) in the following sections. The data presented in tables 3.3, 3.4, and 3.5 for lime, P, and K, respectively shows the percent of under-application, on-target (accurate), and over-application associated with each soil sampling strategy (0.4-ha grids, Soil EC, Soil Optix and Soil Optix Countrate) in each field. It is also important to note that the application data presented in these tables was computed by performing comparisons to the reference application map, which was based on the high-density soil sampling (0.2-ha grids) and assumed to represent the actual spatial variability within each field.

3.4.2 Lime Application Accuracy

As shown in Table 3.3, the 0.4-ha grid performed better than any of the zone methods for lime in all fields except in field 3. In fields 1 and 3, each of the sampling methods provided greater than or equal to 80% application accuracy for lime. The Soil Optix countrate method performed, on average, better than any of the other zone methods across all the fields for lime with an accuracy of 76%, where soil sampling based on soil EC had 73% and Soil Optix had 66% accuracy. Although the 0.4-ha grid performed better than the zone methods, for each of the fields, it also had the greatest amount of soil samples required (7 times or more; Table 3.2) compared to all other methods. It is worth noting that for all fields, except field 4, each of the MZ strategies had greater over-application than under-application, likely meaning these methods are likely recommending lime to be applied in areas where soil pH does not need to be adjusted. This is due to soil sampling in the management zones not depicting the accurate pH value for the zones. This could be due to one of the constraints of this project, the random soil sampling within the zones may not have been an accurate representation of the entire zone.

Table 3.3. Lime application accuracy for different soil sampling methods. Data represents the percent over-application, on-target, and under-application associated with each soil sampling method for all six fields used in this study.

Field	Application	0.4-ha Grids	Soil EC	Soil Optix	Optix Countrate
		------------------------------(%)---------------------------			
1	Over	5	13	13	13
	Target	93	86	80	86
	Under	2	0	7	0
2	Over	4	48	46	48
	Target	86	52	53	52
	Under	11	0	0	0
3	Over	1	4	4	4
	Target	93	96	96	96
	Under	6	0	0	0
4	Over	4	14	29	28
	Target	79	69	37	67
	Under	17	16	34	5
5	Over	7	19	27	27
	Target	87	69	73	73
	Under	6	12	0	0
6	Over	8	34	43	18
	Target	84	65	57	67
	Under	8	1	0	15

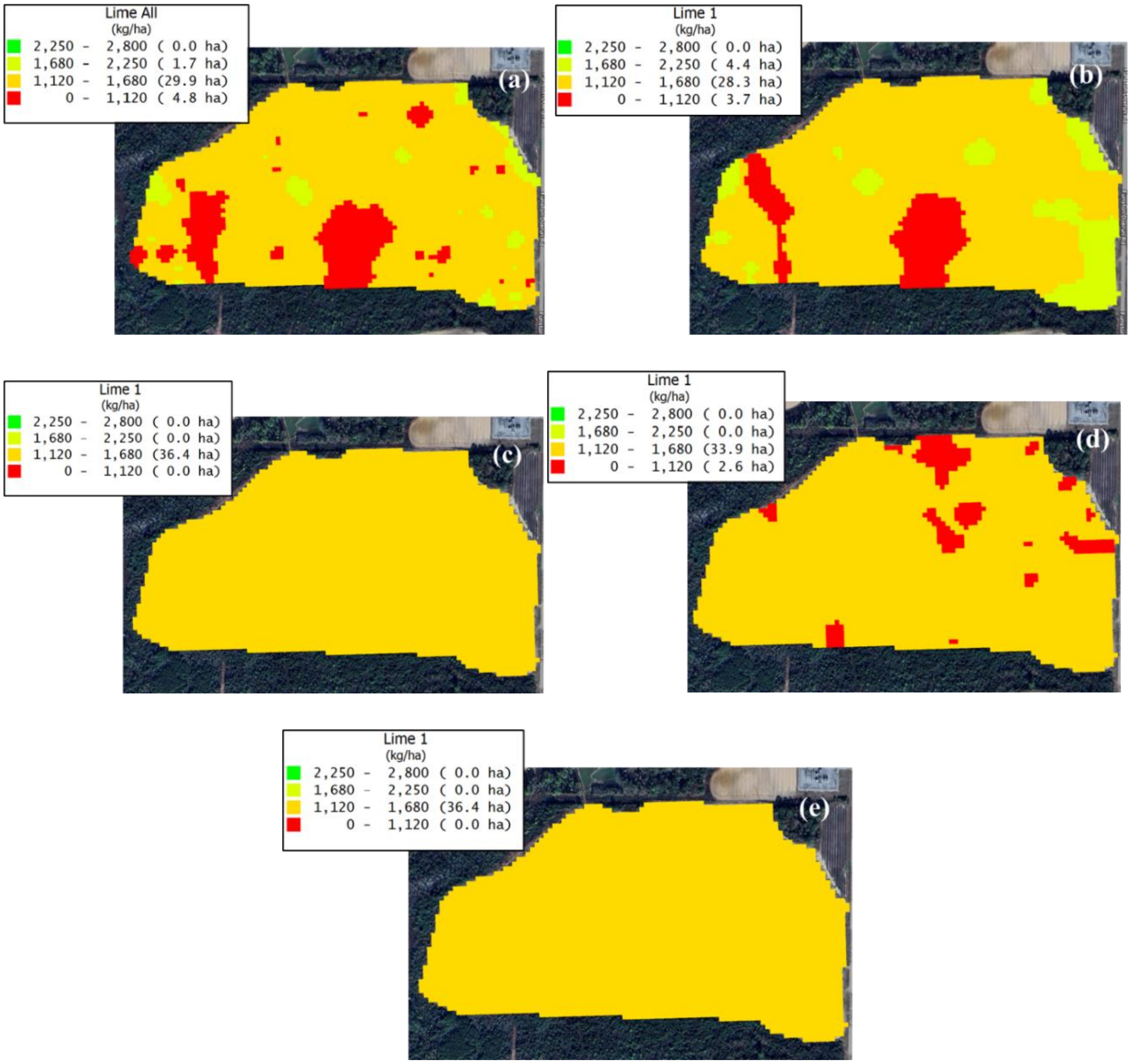

Figure 3.8 (a) depicts the reference lime prescription map based on the 0.2 ha soil sampling whereas (b - f) represents the variable-rate lime prescription maps based on different soil sampling methods for one of the fields as follows: (b) 0.4 ha grid, (c) EC Zones, (d) Soil Optix Zones, and (e) Soil Optix Countrate Zones

Fig. 3.8 depicts the VR prescription maps for Lime in one of the fields in this study. The amount of variability in this field, field 1, is not extremely high, so all soil sampling strategies were at least 80% accurate when compared to the high-density reference map (0.2 ha grids). The prescription map based on 0.4-ha grid samples (Fig 3.8b) closely represents the reference map, some of the areas where the rate changes were slightly bigger or smaller when comparing the 0.4-ha grid map to the 0.2-ha grid map, but, overall, these two maps are closely related to each other. In the MZ maps (c, d, and e), the majority of the field calls for a single rate. In Figures 3.8c and 3.8e, the entire field is one rate, while (d) does have a few small areas where the rate is 0 kg/ha. Looking at it, the map in Figure 3.8d compared to the 0.2-ha reference map (a), the locations calling for 0 kg/ha do not seem to match the areas calling for 0 kg/ha in the reference map.

3.4.3 Phosphorus (P) Application Accuracy

The results for application accuracy for phosphorus can be found in Table 3.4. For fields, 1, 3, 5, and 6, the 0.4-ha grid sampling strategy outperformed all the zone-based strategies. There was high P variability in these fields. While a few zone sampling methods exhibited accuracy levels close to 80% for some fields, such as Soil Optix countrate in Field 1 and EC zones in Field 5, there was no consistent trend that can be found for any of the zone-based strategies, related to chemical properties in the fields. There was minimal to very low P variability in Fields 2 and 4, likely due to historical field management, therefore all the zone-based methods showed almost 100% accuracy when compared to the 0.2-ha grid method. The Rx maps for these fields called for either no application or a single rate application based on the prevalent P levels. For fields 1 and 3, the Optix Countrate performed the best among the MZ strategies, while for fields 5 and 6 the Soil EC MZ strategy was marginally higher than the other MZ methods. There does not seem to be a trend for one MZ strategy to outperform the others, or to be as good or better as the 0.4-ha grid method, across all fields in this study.

Table 3.4 Phosphorus application accuracy for different soil sampling methods. Data represents the percent over-application, on-target, and under-application associated with each soil sampling method for all six fields used in this study.

Field	Application	0.4-ha Grids	Soil EC	Soil Optix	Optix Countrate
		-------------------------------(%)-------------------------------			
1	Over	7	4	1	5
	Target	89	73	78	79
	Under	4	23	21	16
2	Over	1	0	0	0
	Target	99	100	100	100
	Under	0	0	0	0
3	Over	18	7	57	11
	Target	80	61	37	66
	Under	2	32	6	23
4	Over	0	0	0	0
	Target	100	100	100	100
	Under	0	0	0	0
5	Over	10	5	5	10
	Target	89	79	75	72
	Under	1	16	20	18
6	Over	15	42	26	36
	Target	82	56	53	55
	Under	4	3	21	9

Fig. 3.9 displays Rx maps for VR P application for one of the fields used in this study. Similarly to the VR lime map, the 0.4 ha grid sampling has the most similar Rx map to the 0.2 ha reference map. Interestingly, each of the zone-based strategies was able to delineate a zone in the northeastern section of the field that has a similar shape to the reference map. While the nutrient levels in this area may not be exact, it is promising to see the zone methods were able to capture a difference in nutrient levels in this section of the field. It can be noticed that the yellow section in the north part of the Soil EC MZ map (Figure 3.9c) is similar in size and location to the yellow-colored section in the reference map. This same area can be seen in the Soil Optix MZ map (Figure 3.9d), but the nutrient

recommendation for this area is lower for the Soil Optix method when compared to the reference map.

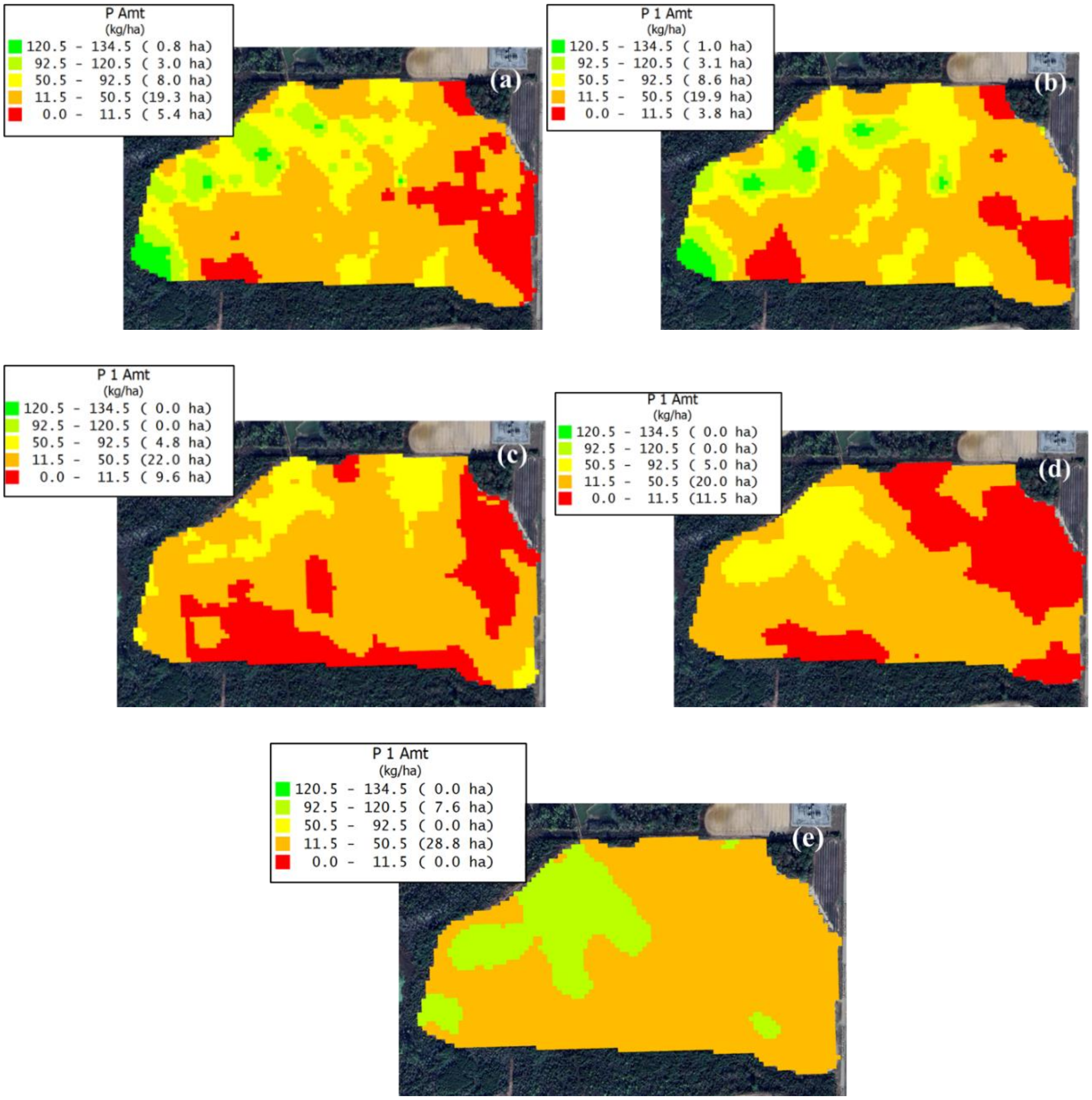

Figure 3.9 (a) depicts the reference P prescription map based on the 0.2 ha soil sampling whereas (b - f) represents the variable-rate P prescription maps based on different soil sampling methods for one of the fields used in this study: (b) 0.4 ha grid, (c) EC Zones, (d) Soil Optix Zones, and (e) Soil Optix Countrate Zones

3.4.4 Potassium (K) Application Accuracy

The application accuracy for K was similar to P in some ways (Table 3.5), fields with more variability exhibited lower application accuracy with the zone-based strategies as compared to the 0.4-ha grid sampling strategy. However, the fields with low variability (Fields 3 and 4) showed high application accuracy for each sampling method. Overlooking fields 3 and 4, only one of the MZ methods had an application accuracy greater than 80% and that was found in field 5 using the Optix Countrate method. The Soil EC method exhibited under-application in all fields. Whereas Soil Optix in all fields (except field 6) resulted in greater over-application than under-application. The Optix Countrate method in field 1 had more over-application, while the remaining fields in this study had a greater amount of under-application.

Table 3.5 Potassium application accuracy for different soil sampling methods. Data represents the percent over-application, on-target, and under-application associated with each soil sampling method for all six fields used in this study.

Field	Application	0.4-ha Grids	Soil EC	Soil Optix	Optix Countrate
		(%)			
1	Over	15	8	26	29
	Target	83	52	73	71
	Under	2	40	2	0
2	Over	11	2	19	8
	Target	83	66	71	74
	Under	5	32	9	17
3	Over	4	0	4	0
	Target	96	94	93	94
	Under	0	6	3	6
4	Over	0	0	2	0
	Target	100	99	97	99
	Under	0	1	1	1
5	Over	3	0	21	1
	Target	91	76	73	90
	Under	7	24	6	10
6	Over	11	4	0	2
	Target	84	70	69	76
	Under	5	25	31	21

Again, the VR Rx maps for one of the fields in this study are shown for K in Figure 3.10. The 0.4-ha grid soil sampling method (Figure 3.10b) produced the most similar map to the reference map (Figure 3.10a). It is worth noting that the 0.2-ha reference map does have some “hot spots” in the center of the map because of the high-density sampling (sampling points located close to each other). There were large differences in nutrient levels between these locations as there is a noticeable soil type transition in this area. The east side is more sandy loam whereas the west side is more clay. Due to the high density of samples and the differences in their nutrient levels, the interpolation created these “hot spots”. As noticed in the 0.4-ha grid sampling method, this area is much more consistent. This does not imply that the 0.2-ha sampling method is incorrect but suggests that it is common for denser sampling points to demonstrate greater variability than larger grids. The Soil Optix map was able to accurately identify the zone in the southern portion of the field where the target rate matched as prescribed by the reference 0.4-ha grid sampling. The Soil EC MZ method also depicted some variability in the field, but the nutrient values were different from the actual nutrient levels depicted by the reference map and recommended either too much or not enough fertilizer in these areas.

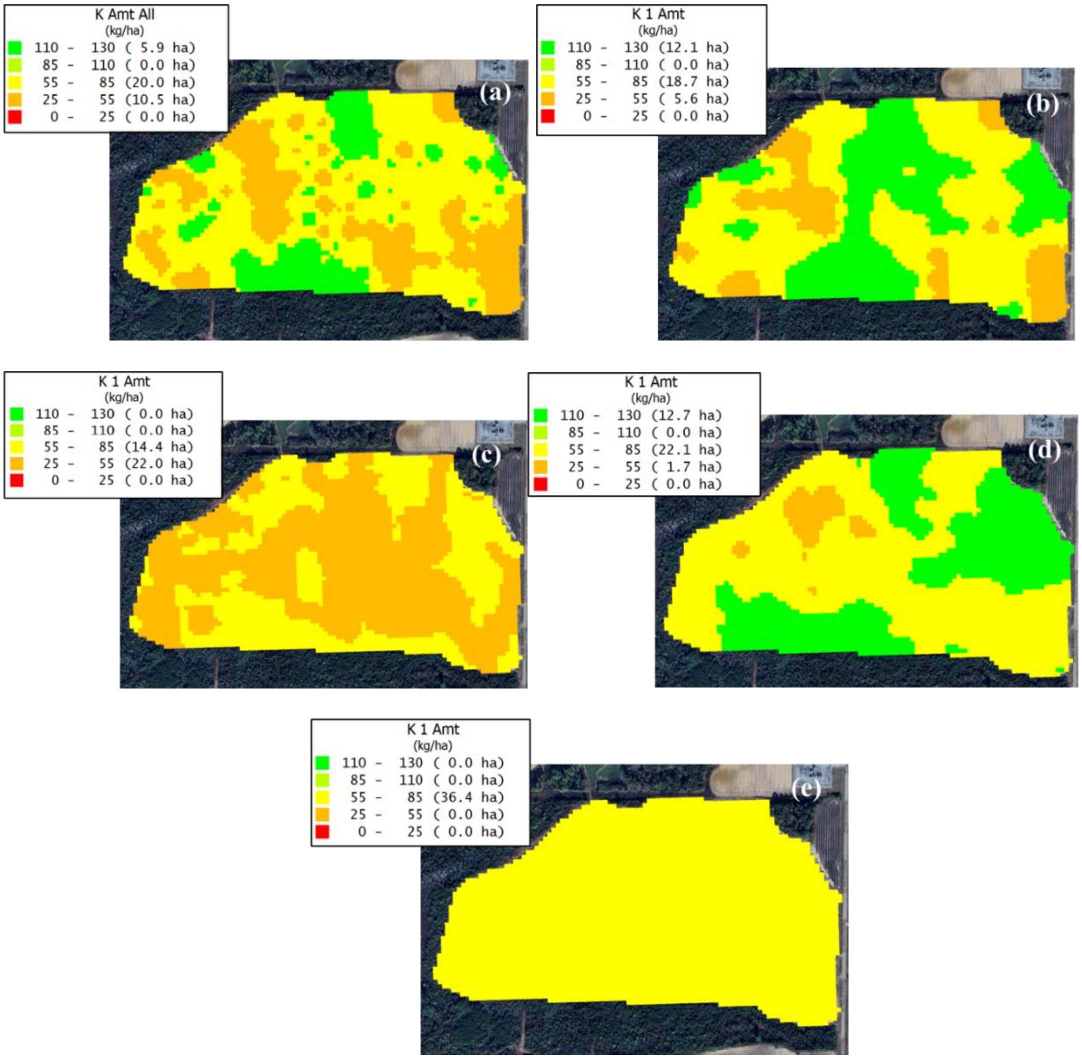

Figure. 3.10 (a) depicts the reference K prescription map based on the 0.2 ha soil sampling whereas (b - f) represents the variable-rate K prescription maps based on different soil sampling methods for one of the fields used in this study.
(b) 0.4 ha grid, (c) EC Zones, (d) Soil Optix Zones, and (e) Soil Optix Countrate Zones

As shown in Tables 3.3-3.5, there is not one particular zone-based soil sampling strategy that stands out above the rest. When looking at the fields individually, there may be a management zone strategy that performs well for a few fields but not great for the remaining. In Table 3.6, the accuracy data is averaged across each of the fields for each nutrient studied in this project, as well as a coefficient of variation (CV) is presented for each method and nutrient. The CV value represents the consistency of the method in accurately depicting soil nutrient levels across the fields. The higher the CV, the higher the variability in the application accuracy across the fields, which means that a particular method worked well in some fields but did not consistently provide the required accuracy in other fields. It is obvious that the 0.4-ha grid sampling has the most accurate application across all nutrients. Thus, the CV is lowest for the 0.4-ha grid sampling method across all fields meaning it is consistently within an acceptable range of 80% accuracy or better. The zone sampling methods all have a CV greater than 14% and most are greater than 20%, meaning they are inconsistent in accurately depicting the soil nutrient levels across multiple fields. While it should be noted the Soil Optix countrate method performed better on average than the Soil Optix method, where the countrate method used fewer soil samples. This could be due to the difference in soil types in the southeastern US compared to in the midwestern US where the Soil Optix algorithm was ultimately developed. This is an important consideration as growers need a method to collect soil samples that can consistently provide accurate data year over year across all their fields.

Table 3.6. Application accuracy of lime, phosphorus (P), and potassium (K) for different sampling strategies. Data is averaged across all fields.

Sampling Method	Lime		P		K	
	Target (%)	CV (%)	Target (%)	CV (%)	Target (%)	CV (%)
0.4-ha Grids	87	6	78	9	90	8
Soil EC	73	21	78	24	76	23
Soil Optix	66	32	74	34	79	15
Optix Countrate	76	21	79	23	84	14

2.5 Conclusions

Variable-rate (VR) applications aid growers in making site-specific management decisions. VR application of lime and fertilizer is widely adopted in the southeastern region of the US. The increasing cost of farm inputs has increased the adoption of VR applications significantly; though this has also led to increased questions and concerns about precision soil sampling methods and their effectiveness. This study was conducted to evaluate the effectiveness of different zone-based soil sampling methods to determine their effectiveness at depicting spatial nutrient variability within six agricultural fields and their influence on the accuracy of VR prescription maps. The zone-based methods were also compared to soil sampling on 0.4-ha grids. Results from this study showed that different zone-based soil sampling methods evaluated in this study (soil EC, Soil Optix, and Soil Optix Countrate), were not able to consistently provide a VR Rx map over 80% accuracy for each nutrient across all the fields. While the zone-based sampling methods did decrease the amount of soil samples collected from each field, the accuracy of the Rx maps was not consistently at an optimum level. Some of the fields in this study show promising results for the delineation of the actual management zones in the fields, but there is still further investigation needed to determine the best way to collect samples within the zones to make sure the nutrient values are representative of the entire zone. Based on this study, collecting soil samples with a smaller grid size (1 ha) should be preferred to better understand the nutrient variability in the field, especially if conducting precision soil sampling in a field for the first time. The grid size in the subsequent years can be increased appropriately to save time and cost if the variability in the field is found to be minimal. While zone-based soil sampling methods have potential and could be easier to implement than grid soil sampling, they need to be studied further in different regions and possibly with different methodologies when it comes to collecting the soil samples within the zones. Further research is also needed to understand how to properly delineate different management zones from different soil properties and historical crop data. Another thing that should be examined would be whether incorporating more spatial data layers into the zone creation process would make the zones more accurate and if certain spatial layers must be considered during the creation of management zones.

CHAPTER 4

CONCLUSIONS

Precision soil sampling methodology is critical to ensure accurate site-specific nutrient applications in agricultural fields. Poor selection of a soil sampling strategy can result in inaccurate and inefficient nutrient applications. Inaccurate Rx maps can create more variability in fields because of over- and under-application of nutrients, which can further make soil sampling and balancing out nutrients in some fields more difficult as time goes on. Soil sampling methodology has been studied for decades, but few studies have been conducted in the southeastern US when it comes to selecting the appropriate grid size or using management zones for soil sampling in agricultural fields. Therefore, this study was conducted to determine the effectiveness of common soil sampling grid and zone methods in depicting spatial nutrient variability and the accuracy associated with their nutrient recommendations.

The first objective of this study was to investigate the effectiveness and economics of different commonly used grid sizes in the southeastern US. In this study, the application accuracy of grid sampling significantly reduced as grid size increased. Overall, greater over- and under-application occurred in the fields with grid sizes larger than 2.0 ha. Grid sizes less than 1.0 ha had application accuracy of greater than 80% for the fields studied, across all nutrients (Lime, P and K). The economic analysis suggested that even with increased soil sampling with smaller grid sizes (< 1.0 ha), it is recommended to choose a smaller grid size to ensure higher application accuracy. The increase in soil sampling locations (number of samples) increases costs but also adds confidence in the application. These findings prove the importance of grid size selection to ensure nutrient applications at the right rate and in the right place.

The second objective of this study was to investigate the use of management zones for site-specific nutrient management. The management zone strategies, used in this study, show a potential to be a feasible soil sampling method for growers, as trends were found when comparing the nutrient maps to a high-density reference map, that there was a good correlation between nutrient maps based on zone sampling and reference map, but the nutrient values were either high or low. Further research should be conducted to determine the best method for selecting sampling locations within the zones to increase the application accuracy of the management zones. It would also be beneficial to explore other spatial data layers that could be added to these zone delineation methods to better understand the variability within the fields, such as elevation, aerial imagery, etc.

In conclusion, the findings from this research show the importance of precision soil sampling methodologies and their impact on site-specific application of soil amendments and nutrients. By selecting the appropriate soil sampling strategy and informing accurate site-specific nutrient management, growers can minimize input costs and optimize yields within the fields. Continued research in soil sampling techniques is essential for further advancing precision agriculture on farms in the southeastern US.

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