DEVELOPMENT OF MOISTURE SENSOR TECHNOLOGY TO ENHANCE CONVEYANCE AND FIELD DISTRIBUTION OF BROILER LITTER

by

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ABSTRACT

As environmental implications for land application of poultry litter become stricter, technological advancements on litter spreaders will be required to improve field performance. The inherent physical variability, moisture content and bulk density, in poultry litter makes land application difficult with spinner-disc spreaders. The overall goal of this research was to identify and develop technology to provide moisture and/or density feedback to a spreader, rate controller for enhancing litter conveyance and distribution during field application. The research objectives were to evaluate the: 1) effect of bulk density (moisture content) on metering and placement of broiler litter when using a spinner-disc spreader, 2) ability of a capacitance type moisture sensor for real-time moisture measurement in broiler litter, and 3) feasibility of near-infrared (NIR) spectroscopy for predicting moisture content in broiler litter. Results indicated that high discharge rate errors (>±15%) and statistical differences in distribution patterns ($p<0.05$) at a few transverse positions were determined when incorrect density values were used within a rate controller. Density treatments affected mass flow by the conveyor which further impacted the application rates and distribution patterns. These results suggested the use of the correct density value within a spreader rate controller to maintain application accuracy. The inclusion of real-time moisture or density information as a feedback to the rate controller to account for moisture/density variations was thereby proposed. Results for evaluation of capacitance type moisture sensor indicated that the sensor generated a linear response within the 16%-31% moisture range at the nominal (loose) bulk density of broiler litter. The sensor output was

impacted by litter density and the operating moisture range further decreased as wet bulk density increased. Validation of the regression models relating sensor output to litter moisture content showed a strong linear relationship (R^2 = 0.90-0.94) and low standard errors (<1.2%). The results suggested that a properly calibrated sensor has good potential for real-time moisture measurements in broiler litter but density impact on sensor performance must be considered. Evaluation of NIR spectroscopy indicated that absorption bands within the 1400-1440 nm and 1900-1950 nm wavelength regions were strongly correlated (R^2 = 0.97-0.99) to litter moisture content. Spectral data analysis indicated that the absorbance values at 1400 nm plus 1900 nm or at 1930 nm can be independently used for real-time moisture determination in broiler litter. Overall, the NIR technique was recommended for real-time moisture measurement in broiler litter because of its rapid, non-destructive, non-intrusive and density-independent measurements. In the future, development and inclusion of a real-time moisture measurement technology, such as NIR, on a litter spreader will help improve litter conveyance and distribution during application.

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CHAPTER ONE

INTRODUCTION

1.1 PREFACE

21st century agriculture faces challenges of producing the food, fiber and energy to feed a growing world population along with adopting more efficient and sustainable production methods which conserve natural resources and maintain healthy ecosystems. Projections by the Food and Agricultural Organization (FAO, 2010) indicate that feeding a world population of 9.1 billion in 2050 would require raising overall food production by 70% between 2010 and 2050. Ninety percent of the growth in crop production globally is expected to come from higher yields and increased cropping intensity, with the remainder coming from land expansion (FAO, 2010). New agriculture technologies and improved farming practices are needed to improve crop productivity and product stewardship to meet these demands. The world's options for increasing crop production are limited both by the supply of land and water. Therefore, the role of fertilizer in achieving intensified production and increased crop yield is undeniable. Accurate placement of fertilizer not only improves nutrient use efficiency by crops, but also lowers production costs while ensuring sound environmental stewardship.

Achieving a balanced nutrient management approach along with maintaining environment quality remains a challenge when trying to develop best management practices for effectively using fertilizer. Management of P and N can be difficult at times due to equipment limitations. Further, for increasing crop production to support a growing population and rapid economic growth, improving fertilizer use efficiency becomes an important task to ensure food security, social stability and environmental quality. This goal can only be reached with enhanced nutrient management practices and improved application technology for fertilization. Successful fertilization strategies include using available organic nutrient resources wherever possible, maintaining balanced fertilization to support increased crop yields, develop advanced technology to improve fertilizer use efficiency such as slow release fertilizers, site-specific nutrient management, etc., and developing optimal 4R Nutrient Stewardship practices (Right source, Right rate, Right time, Right place) and best management practices for irrigation, cultivation and other agricultural practices. The use of poultry litter as an organic nutrient resource for fertilization to meet soil-crop nutrient requirements has been increased considerably over the past years. The primary reason has been the escalating prices of inorganic fertilizers. Fertilizer prices have increased by more than 50% over the last 10 years (ERS-USDA, 2011).

The use of poultry litter as a valuable source of nutrients and organic matter for agricultural soil-crop systems has been proved to increase crop yields and soil quality. Poultry production in Alabama produces approximately 2 million tons of poultry litter annually (Mitchell and Tyson, 2007). Poultry production regions have been accompanied by environmental issues related to land application over the years. Dense poultry production, especially in northern half of Alabama, has resulted in over-application of litter. Environmental issues due to repetitive application on the same land have focused research studies and efforts towards more efficient management and application of litter. Current environmental concerns focus on offsite transport of P and N from crop-pasture land. Future technology and input application equipment must accurately meter and distribute litter in order to meet local or site-specific crop and soil requirements to reduce over-application issues.

Best management practices (BMPs) along with precision agriculture (PA) technologies such as variable-rate technology (VRT) have the potential to enhance environmental and nutrient stewardship. For incorporating PA technologies, rate controllers and guidance systems are increasingly used for improved application control on spinner-disc litter spreaders. However, the large natural physical variability in poultry litter makes it difficult to achieve accurate metering and distribution uniformity even through the adoption of these technologies. The high variability in commonly available litter, particularly in moisture content and bulk density, can produce high, undesirable application errors during spreading. Bulk density for poultry litter is related to its moisture content like other biomaterials (Malone et al., 1992; Glancey and Hoffman, 1996). Accurate measurement of one or both of these parameters can help in maintaining target rates during field application. This research makes a step towards the concept of real-time moisture measurement on litter spreaders by testing the hypothesis that moisture or density variations within a litter load can affect metering and thereby the application rate and distribution during application. Besides land application, the development of real-time moisture sensing technology would also help in better litter management related to its handling, transportation and storage. Knowledge and the ability to measure real-time moisture, especially during conveyance, will help improve the design, selection and operation of litter management systems.

1.2 JUSTIFICATION

Limited research has been conducted to thoroughly investigate the application of poultry litter (metering and distribution) using spinner-disc spreaders. Most research studies have used synthetic fertilizers, such as urea, potash, etc., with limited studies focused on spreading organic fertilizers. The reasons behind the lack of research on applying organic fertilizers has been their perceived low economic value to crop production, low density making transportation expensive, and many times perception as a waste product versus fertilizer source. With the current poultry production in Alabama and the environmental concerns related to over-application of litter, measures have been initiated to improve the distribution of poultry litter during application with more states implementing regulations for adoption of BMP's and basing litter application on P recommendations instead of N. The phosphorus index (P index) tool has been increasingly utilized to assess the risk of P movement and make better P application decisions. Nutrient stewardship programs such as The 4R's to Nutrient Stewardship in conjunction with recent precision agriculture (PA) technologies have the potential to reduce over-application issues and provide accurate delivery of inputs plus sound practices to meet local crop or soil requirements.

Spinner-disc spreaders are the most common equipment used to apply litter to crop and pasture lands. The main goal when applying litter with spinner spreaders is to maintain accurate metering and uniform distribution. Material physical properties and spreader parameters are important factors that influence performance during field application. The important physical properties that can affect litter handling and spreading are particle size, bulk density, moisture content, angle of repose, and static friction. Among these properties, moisture content is considered important since it affects other physical properties as well. In the case of poultry litter, the large variability in its physical characteristics like particle size, moisture content, bulk density etc. makes it difficult to maintain acceptable spread uniformity in the field. Further, maintaining target application rates can be challenging due to this inherent variability.

Considerable research has been reported on the influence of litter moisture content on its physical properties. Malone et al. (1992) reported an increase in wet bulk density of litter from 432 to 545 kg/m^3 with an increase in moisture content from 27% to 32%, respectively. Glancey and Hoffman (1996) concluded that moisture content significantly increased the static coefficient of friction and wet bulk density, and indicated the importance of measurement and knowledge of the right moisture content for design and working of material handling systems for poultry litter. Similarly, Thirion et al. (1998) reported that the bulk density of different manures obtained from a variety of origins (animals, housing, etc.) was dependent on dry matter content of the manures with bulk density as the main factor affecting the discharge rate of spreader. The compressibility of poultry litter is also affected by moisture content (Bernhart et al., 2008). Based on feeding and type of management systems for production houses, moisture content in commonly available poultry litter can vary between 15% and 40% (Lague et al., 2005). This large variability can cause a significant density variation within a batch of litter ultimately impacting the amount applied and distribution uniformity during field application. High moisture content also poses problems of caking and material buildup on spinner-discs while spreading. Material build-up impacts material flow on the spinner-discs, thereby affecting litter distribution. Therefore, researchers have emphasized the need for measurement and knowledge of the right moisture content for litter application along with technology development to continuously sense and monitor the flow rates on spreaders to match target application rates with spatial soil-crop requirements.

Knowledge of the correct litter moisture and density is also important when considering application because density is one of the required setup parameters in a rate controller. A rate controller on a spreader helps to improve control and management of litter application in the field. The rate controller maintains the target application rate based on initial user input and feedback parameters (Figure 1.1). Input spreading parameters (target application rate, gate area, swath width, and litter density) are manually entered in the controller setup menus by the operator before application. These parameters remain constant throughout the spreading period for a single rate application. If variable-rate capabilities exist with the rate controller, the application rate will change during field operation according to the prescription (R_x) map loaded into the rate controller. A DGPS receiver or radar provides ground speed as a feedback parameter. The controller calculates the desired conveyor speed based on these parameters and maintains this speed to deliver the target application rate. During field operation, the controller also receives continuous feedback from the conveyor roller shaft sensor (encoder) and makes conveyor speed adjustments accordingly.

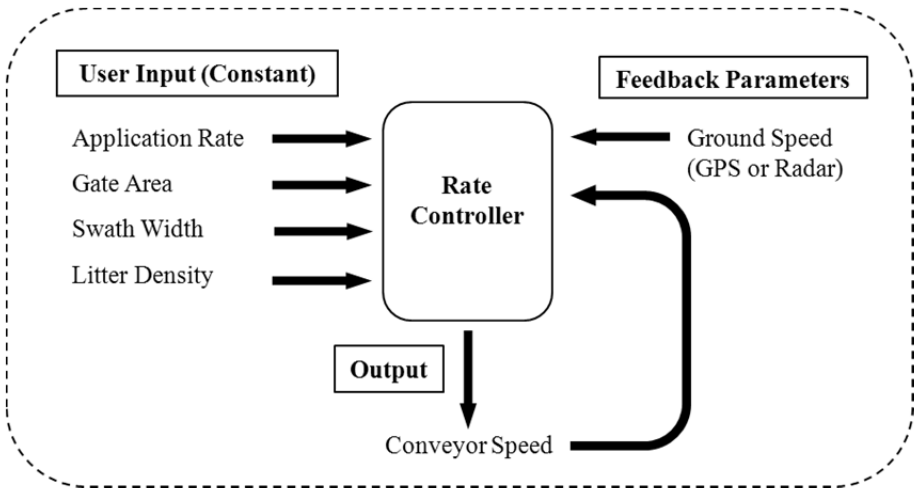


Figure 1.1. Diagram indicating user input and feedback parameters (i.e. ground and conveyor speed) for a typical rate controller used on litter spreaders.

Considering the variation in litter density due to varying moisture content, a rate controller will apply off-target rates frequently since only a single density value is established within the setup menu. Therefore, any density variations in the litter are not accounted for during application. Further, concerns can exist when performing variable-rate application (VRA) of litter since multiple rates are applied within the same field.

This research is based on the idea that an inline moisture or density measurement technology can be used to provide secondary feedback to a spreader rate controller for updating real-time density values. The secondary feedback can be used for managing the target application rates better as litter moisture or density varies. Such a feedback technology could also assist in making spreading decisions if litter has to be applied within a specific moisture range. Different types of inline moisture measurement techniques such as capacitive, NIR and microwave techniques have been evaluated and used by researchers in the past for measuring small to large moisture variations in biomaterials. But no attempt has been made to measure litter moisture on a real-time basis during field application.

1.3 Objectives

The overall goal of this research is to improve litter application with spinner-disc spreaders. This improvement can be achieved with the idea that using real-time moisture and/or density information in a rate controller can help reduce off-rate application errors by maintaining target rates for broiler litter since moisture/density variations can exist within the same load of litter. The objectives of this research were to:

1. Evaluate the influence of broiler litter bulk density on metering and distribution when applied using a spinner-disc spreader.
2. Determine the potential of a capacitance type moisture sensor for measuring real-time moisture content of broiler litter.
3. Determine if absorption spectral values at individual wavelengths within the near-infrared (NIR) spectra can be used for real-time moisture measurement of broiler litter.

1.4 Organization of thesis

This thesis is presented in manuscript format. Chapter 1 provides introductory statements justifying the focus of this research including the overall research objectives. Chapter 2 presents a review of literature outlining prior research and background on the physical properties of broiler litter, environmental issues related to its land application, spinner-disc spreaders and various inline techniques for moisture measurement in different biomaterials including poultry litter. Chapter 3 covers the evaluation of bulk density effect on the metering and distribution of broiler litter with spinner-disc spreaders. Chapter 4 presents the evaluation of a capacitance-type moisture sensor for moisture measurement of broiler litter while chapter 5 reports the evaluation of NIR spectroscopy for real-time litter moisture measurement. Chapter 6 summarizes and discusses the results for this research. Finally, Chapter 7 presents the overall conclusions and suggestions for future work.

CHAPTER TWO

REVIEW OF LITERATURE

Over the past several decades, there has been considerable research conducted to help gain a better understanding of the variables affecting the spreading of organic and inorganic fertilizers. Most of that research has been focused on understanding material and machine variables that could improve the application of organic fertilizers. Several publications were reviewed to gain knowledge on the characteristics of organic fertilizers especially poultry litter. These articles included physical properties, calibration standards, environmental issues related to poultry litter along with its distribution patterns and uniformity during field application. However, limited information is available on real-time determination of litter properties, especially moisture content and bulk density, and the effect of these properties on litter application. Publications related to various moisture measurement methods, those mostly used for biomaterials (e.g. corn, hay and forage), were reviewed to determine the potential application with poultry litter.

2.1 POULTRY LITTER

Alabama's poultry industry produces nearly 2 million tons of litter annually (Mitchell and Tyson, 2007). This production is mostly concentrated in the northern half of the state with houses located densely in small areas. Therefore, most of the produced litter is applied near these facilities because of high transportation costs, leading to over-application within the same fields. The over-application has resulted in higher levels of phosphorus in surface water posing environmental concerns. These environmental implications due to excessive land application have led to various studies and research efforts to manage and apply litter more efficiently. The litter, a combination of manure and bedding material such as pine shavings or peanut hulls, is utilized as fertilizer by applying it to crop and pasture lands. It is a good source of nutrients and phosphorus content along with dry matter. Poultry litter is extremely variable in terms of its physical characteristics which makes it difficult to land apply.

2.1.1 PHYSICAL PROPERTIES

The physical properties of material being utilized are important factors affecting the process of handling and spreading in agriculture. Poultry litter is a bulk solid. Bulk solids are composed of many particles of varying sizes (and possibly slightly varying shape), chemical composition, and densities, that are randomly grouped together in order to form a bulk (Woodcock and Mason, 1987). Therefore, the characterization of bulk solid behavior involves characterizing the individual particles that comprise the bulk material. Individual particle properties of interest include particulate size, shape, particle density and surface area, while the bulk properties needed to characterize poultry litter include bulk density, flow properties, compressibility, and moisture content. Knowledge of these properties is needed to optimize the conditions required to process, handle and transport litter. Accurate determination of these properties is a real challenge due to large physical variability found in poultry litter. Various researchers have investigated and characterized the physical properties for different litter handling operations.

2.1.1.1 PARTICLE SIZE

Size is considered as the most important characteristic of particulate materials because it characterizes other physical properties and behavior. Ndegwa et al. (1991) investigated the fractionation of poultry litter for enhanced utilization. A vibrating screen was used to fractionate the litter and the material was separated into three fractions: (1) particles greater than a standard No.6 mesh screen (3.3–mm opening); (2) particles smaller than a standard No.20 (0.83–mm opening); and (3) particle sizes between the above two. They reported that the fine fraction accounted for 26% to 41% of the litter sample; the middle fraction 47% to 41%; and the coarse fraction 27% to 18%, depending on the number of flocks raised on the litter. Koon et al. (1992) studied the particle size distribution and chemical composition of broiler litter. A standard set of sieves No.4 through No.100 and a vibrating shaker were used for separating litter samples. They concluded that there was little variation in the particle size of pine shavings in poultry litter over a four grow-out period and majority of the litter was retained on the larger sieves [No.50 (0.297 mm) or larger]. Nutrient concentration for each of the macronutrients (N, P & K) increased as the particle size decreased. On the other hand, Wilhoit et al. (1993) found that carbon concentrations increased with increasing particle size of litter and N content was relatively uniformly distributed within different size fractions.

Landry et al. (2003) quantified the particle size for different types of manure including poultry litter ranging from 10% to 50% on wet mass basis. They reported that the average geometric mean length for poultry manure at 34.5%, 41.5% and 47.3% TS levels was found to be 18.9, 14.2, 10.9 mm, respectively. Bernhart et al. (2009) analyzed the particle size distribution for poultry litter using a standard set of sieves (1.700 to 0.212 mm) and a vibratory shaker. Most of the particles (24.14% and 20.19%) were retained on the bottom pan and sieve with an aperture of 0.850 mm, respectively. The mean diameter of poultry litter was determined to be 0.841 mm and particle sizes below 0.400 mm (40% of the litter) were considered fine and compressible.

2.1.1.2 MOISTURE CONTENT AND BULK DENSITY

For organic solid materials like poultry litter, there could be a considerable change in moisture content and bulk density in the process of handling and storage depending on its exposure to rainfall and other climatic conditions. Moisture content and bulk density are also important physical properties which significantly influences other properties of poultry litter such as flowability and compressibility. The change in these properties due to characteristic variability in litter may have a profound effect on litter application in the field.

Poultry litter can have high moisture variability when cleaned out from a house varying from dry to wet depending upon location in the house. Malone et al. (1992) investigated the quality and quantity of poultry manure in Delmarva broiler houses under different management programs. Their data indicated that the wet bulk density of clean out manure, on average, increased from 432 kg/m^3 to 545 kg/m^3 as the number of flocks grown in the house increased from a low of 1 to 6 flocks to a high of 13 to 18 flocks, respectively. Manure moisture content in total cleanout manure, on average, increased from 27% to 32% wet basis as the number of flocks increased from a low to high number of flocks. Up to the sixth flock, crust out wet bulk density and moisture was, on average, 513 kg/m^3 and 37% wet basis, respectively. Koon et al. (1992) closely monitored the moisture content in poultry litter pine shavings during four growouts. They determined a low of 17.4% after the first week to a high of 22.5% after the seventh week. They also reported that litter exposed to higher moisture content during the growout might exhibit a different particle and nutrient distribution pattern.

The importance of litter moisture content and number of flocks raised on the litter, when trying to attain uniform application considering mass and nutrient content, was determined by Jenkins (1989). Glancey and Hoffman (1996) conducted a study on physical properties of poultry litter. The investigated properties for five different types of poultry litter and three types of compost were bulk density, angle of repose, maximum lump size and static coefficient of friction. Tests were conducted on fresh poultry clean-out and crusted material, crusted and clean-out poultry litter stored for 5 weeks and 14 weeks, and fresh composted material under three conditions: poultry manure composted with dead chickens, municipal solid waste (MSW) composted with dewatered sludge, and MSW composted with poultry litter. Results showed that outside storage and exposure to rainfall for all types of manures significantly increased the moisture content, static coefficient of friction and wet bulk density with the majority of the increase being within the first 5 weeks of outside storage. They also evaluated the dependence of wet bulk density on moisture content across all the solid wastes. Their results implied that measurement or knowledge of moisture content was more important than the type or source of waste material for design and analysis of waste material handling systems. Wilhoit et al. (1993) also emphasized that litter moisture content and number of flocks raised on litter can play a significant role when trying to attain uniform application.

Thirion et al. (1998) investigated the physical characteristics of 25 different types of animal manure including poultry litter and their impact on performance of the spreader. The measured parameters were bulk density, cohesion, shear stress resistance, dry matter content, straw content and friction coefficient. They also analyzed the relationship between these properties and spreader performance to confirm the usefulness of these measurements. The three main relationships verified were: density and discharge rate, shear stress resistance and drive torque, and heterogeneity and spreading precision. Results showed that bulk density of the manures obtained from a large variety of origins (animals, housing, etc.) varied within the same batch and it mainly depended on dry matter content of the litter. Both high (900 kg/m^3 to 1000 kg/m^3) and low (300 kg/m^3) densities were mainly observed for chicken manure. The dry matter content for most of the manures ranged from 16% to 53%. Results illustrated that bulk density was the main factor that affected the discharge rate of the spreader.

The physical and rheological properties for different types of manure, ranging from moisture content of 10% to 50% (wet basis), was studied by Landry et al. (2003). The selected properties included total solids concentration, bulk density, particle size distribution, friction characteristics and shearing behavior. These properties were measured for dairy cattle, sheep, poultry and pig manure. Total solids (TS) concentration provides another means of reporting dry matter content or moisture content of a material. The original total solids concentrations of the dairy cattle, sheep and pig manure samples were around 15%, 30% and 25%, respectively. For poultry manure, two different levels of TS were observed (12% and 18%) depending on the amount of water obtained from leaking drinkers. The measured bulk densities for poultry manure were 607.5, 884.7, 1028.2 and 1091.8 kg/m^3 at 50%, 40%, 30% and 20% TS levels, respectively. These researchers suggested that the range of values presented for different manures can be properly used in the design and analysis of manure handling and land application systems.

Lague et al. (2005) reviewed some of the physical, chemical and biological characteristics of livestock manure as they relate to land application operations. They reported that the dry matter content of the manure can vary over a wide range depending upon the feeding and manure management systems that are used on a particular livestock operation and this variability has a direct impact on the operation of the handling and land application systems. The dry matter content (w.b.) for poultry litter can range from 12.0% to 25.6% for freshly excreted manure (layer) and 60.8% to 89.1% at the end of the production cycle for broiler litter. For land application operation, the main objective is to supply the soil-crop system with a controlled application rate of manure. The continuous monitoring of manure flow rate on semi-solid and solid manure application equipment is difficult because of the heterogeneous nature of the product and of the often non-uniform loading conditions of the spreaders. The researchers recommended the need for technology development to continuously sense and monitor manure nutrient content and flow rate on land application equipment in order to match the nutrient application rates with spatial soil-crop requirements.

The effect of moisture content on selected physical properties of poultry litter was also investigated by Bernhart et al. (2009). The investigated properties were: particle and bulk density, tap density, Hausner ratio, and porosity. Results illustrated that increasing the moisture content resulted in a decrease in poured bulk density, particle density and porosity. The poured bulk density of poultry litter ranged from 0.551g/mL to 0.533g/mL within the moisture content range of 10.3% and 30.6% respectively. They also mentioned that the poured bulk density of poultry litter (0.50g/mL) was significantly higher than the values typically observed for agricultural materials (less than 0.20 g/mL). Their results implied that in process design applications, the amount of volume required to store poultry litter will increase as moisture content increases.

Several other studies have shown the effect of moisture content on the physical properties of biological materials (Balasubramanina, 2001; Barbosa et al., 2005). Moisture content significantly influences the flowability of bulk solid materials (Woodcock and Mason, 1987). Flowability represents a measure of the cohesiveness and adhesiveness of bulk solids and is influenced by other bulk properties such as bulk density, porosity and compressibility. For poultry litter, knowledge of the equilibrium moisture behavior is needed to manage and prevent its spoilage during storage, which may reduce the fuel value and quality of the litter (Jenkins, 1989).

Pelletizing is one of the effective ways that has been used to increase the value of agricultural and biological materials. There have been several efforts to densify poultry litter by pelletization (McMullen et al., 2005; Lichtenberg et al., 2002). McMullen et al. (2005) measured the physical characteristics of pellets from poultry litter within a moisture range of 6% and 22%. Results showed that bulk density and particle density of the pelleted litter decreased and increased, respectively with increase in moisture content. Durability of the pellets also reduced as moisture content increased. They reported that bulk density of the litter increased by four fold through pelleting. Lichtenberg et al. (2002) also reported that pelleting can be used to increase litter density by more than three fold.

2.1.1.3 COMPRESSIBILITY

Unintentional compression of bulk solids can be undesirable during storage, handling and transportation, because it often leads to issues related to flowability. The compression of bulk solids can be caused by vibrations during transportation and/or static weight of the material itself (sometimes called mechanical compression) (e.g. during storage). Colley et al. (2005) studied the compaction behavior of poultry litter and switchgrass. They reported that temperature, moisture content and die size significantly affected the density of switch-grass and poultry litter pellets. The density of the pellets decreased as moisture content increased. A comparison study indicated that poultry litter compacted to a higher density than switchgrass due to higher mineral content and initial bulk density.

Bernhart et al. (2009) reported that the percent compressibility of poultry litter ranged from 2.5% to 18.0% with sample moisture contents of 10.2% and 30.9% respectively. Increasing the moisture content of the poultry litter reduced its flowability (hence increased particle cohesion) from easy flowing (flow index of 6.369) at a moisture content of 10.3% (w.b.) to very cohesive/non-flowing (flow index of 1.871) at a moisture content of 30.9% (w.b.). The adhesion of poultry litter to the milled steel surface was reduced when the surface was modified. The carbon coated steel surface had the least adhesion in comparison to the aluminum surfaces and mirror finished steel surface.

2.1.2 NUTRIENT MANAGEMENT AND ENVIRONMENTAL ISSUES

Many researchers over the years have studied ways to more efficiently manage broiler litter as a fertilizer (Wood, 1992; Coloma et al., 2004; Mitchell et al., 2007). Coloma et al. (2004) and Wood (1992) both suggested combining litter with an inorganic N fertilizer before applying. Wood (1992) also stated that poultry litter has a high nutrient content compared to other manures and can produce equivalent yields as synthetic fertilizers but at lower costs. Mitchell et al. (2007) stated the need for a Comprehensive Nutrient Management Plan (CNMP) on every farm and the requirements needed to apply this plan when addressing nutrient management issues to protect water quality. There were five steps to this CNMP. The first step focused on estimating broiler litter amount, compost production, and storage facilities. The second step was to estimate the nutrient value of the litter and compost. Next, map and calculate land area for spreading using an aerial photo or topographic map. Next, determine the crop and nutrient needs for each field using the recent soil tests. The final step was to determine uses for excess litter and compost.

Armstrong et al. (2006) examined irregular soil sampling on a field of long-term litter application to predict the areas of accumulation and loss of nutrients in a field. They determined that by using irregular soil sampling points and focusing on topography and landscape of a field, nutrient accumulation after long-term litter application can be determined. Wood (1992) determined the severity of litter application to the landscape and found that long term litter application resulted in excessive nitrate leaching and degraded the environment.

Nitrate leaching and P runoff are the two major environmental concerns when discussing poultry litter application. Excessive consumption of leached NO_3 into groundwater can have harmful effects on humans as well as livestock (Wood, 1992 and Armstrong et al., 2006). Farmers often apply litter to meet the N requirement of their crop; however, in doing so they can over-apply P. This over-application leads to a buildup of P in the topsoil and, through runoff and erosion makes it to surface water as a pollutant. The Phosphorus Index (P index) is a commonly used tool utilized to assess the risk of P movement into surface waters and make better P application decisions (USDA-NRCS, 2001). Excess poultry manure nutrients (N and P) from high deposition rates have been implicated as nonpoint pollution sources to groundwater and surface water (Leibhardt et al., 1979; Weil et al., 1977). Therefore, more states are basing litter application on P recommendations instead of N to meet environmental regulations.

The NRCS Code 590 (USDA-NRCS, 2002) was created to manage all aspects of nutrient application to the soil by setting regulations on timing, amount, source and placement of nutrients. The specific regulations that pertain to the application of poultry litter in Alabama are: application should be 15.24 m from surface waters of the state, 30.48 meters from the nearest occupied dwelling, church, school, hospital, park, or non- potable water wells, 61 meters from Outstanding National Resources Water, Outstanding Alabama Water, potable water wells, or public water supply. All precautions should be taken to eliminate or minimize nonpoint source pollution to the ground and surface waters. Each site, farm, or field shall be evaluated using the P index and the Leaching Index to assess the movement of applied nutrients in the soil to protect the quality of the water resources in the state. A soil test must be conducted using either the

Auburn University Soils Testing Laboratory or an acceptable laboratory to determine the allowable amount of nutrients that can be applied. Soil tests older than three years shall not be used for nutrient planning. It is recommended that soil amendments, such as lime, shall be applied to adjust soil pH to the specific range of the crop for optimum availability and utilization of nutrients. Regulations regarding nutrient application states that the application of nutrients needs to be based on current soil test reports and that the application shall not exceed 10% of the intended rates of the field. When applying organic by-products, such as poultry litter, the acceptable rate is generally based on the amount of P that can be applied to the soil due to the P index rating of the field. When the vulnerability rating (P index rating) is very low/low, litter can be applied to meet the N requirement even if it means the P rating exceeds 10% of the established application rate. Organic by-products cannot be applied in Alabama during the fall and winter seasons unless it is on actively growing crops. In north Alabama, no application can occur between November 15 and February 15 due to crop inactivity.

Also, best management practices (BPM's) for litter including means to improve field application are being promoted. Fertilizer companies and environmental agencies such as USDA-NRCS are promoting environmental stewardship programs (e.g. 4R's to Nutrient Stewardship) to reduce environmental risks due to fertilization of litter. The 4R's relates to four different aspects of application and provides a framework to assess whether the 'Right Source' is applied with the 'Right Rate' at the 'Right Time' and in the 'Right Place' to ensure accurate metering and placement of materials while reducing environmental risks. This approach helps to identify the opportunities to improve material efficiency. The 4R's concept along with recent precision agriculture technologies such as variable-rate (VR) also provides the basis to improve litter spreading thereby reducing the risk of offsite nutrient transport.

2.2 Spinner-Disc Spreaders

2.2.1 Overview and Components

Spinner-disc spreaders are the most common equipment to land-apply fertilizers (Figure 2.1). These pull-type spreaders are equipped with hydraulically controlled apron chain and dual rear spinner-discs with four uniformly spaced vanes on each disc (Figure 2.2). A rear gate opening on spreader hopper controls the volume of material on the conveyor by allowing a vertical adjustment of the gate (Figure 2.2). The conveyor chain delivers material from hopper onto the spinner-discs, where rotating motion of discs disperses the material in semi-circular pattern behind the spreader. Proximity sensor mounted under one or both of the spinner-discs provides continuous speed feedback and helps maintain disc speeds during application. The conveyor shaft speed is controlled by an encoder, coupled directly to the front or rear shaft of the apron chain, to deliver target rates. A rear divider is usually provided to adjust the drop location of material onto the spinner-discs (Figure 2.2).

Figure 2.1. Typical spinner-disc spreader used for litter spreading.

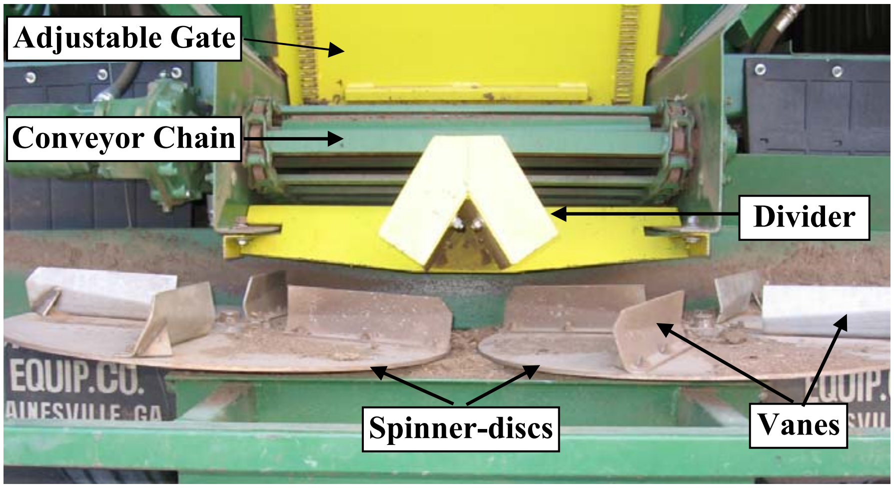


Figure 2.2. Spreader components: spinner-discs, divider, conveyor chain and adjustable gate.

A key goal when applying fertilizers with spinner-disc spreaders is to maintain spread uniformity and accuracy. The popularity of these spreaders for application of organic and inorganic fertilizers has initiated research efforts focusing on studying various machine parameters which can be adjusted to improve performance during application. These parameters fall basically into three categories (Ling, 1997): (1) the parameters that control the material metering such as the conveyor type, width, speed and gate opening; (2) parameters that control the delivery point of material onto the spinner-disc including shape, dimension and location of the flow chute; and (3) parameters that directly control the distribution of material such as disc configurations (number and type of vanes, disc diameter and angle), disc position and disc speed. Therefore, various research attempts have been made to better understand these machine parameters that can influence material spread uniformity. Most of these studies focused on manufactured fertilizers such as urea, potash, or blends, with only few focusing on organic fertilizers, such as poultry litter.

2.2.2 Calibration and Evaluation Standards

Calibration is important to determine the fertilizer application rate and uniformity at which a spreader should be operated and is a key component in maintaining target rates. It also helps in setting hardware and software when using the latest technologies such as VRT. Fulton et al. (2005b) found that pattern adjustments could be made to improve distribution patterns for all applicators and that generating overlap patterns during calibration can usually correct off-target application while quickly quantifying application uniformity. Proper calibration can also reduce environmental risk associated with applying poultry litter (Mitchell and Tyson, 2001). Marsh et al. (2003) stated that it is important to apply manure at the desired rate to meet the nutrient requirements of a specific crop.

The American Society of Agricultural and Biological Engineers (ASABE) Standard, S341.3 (2004) outlines the procedure for measuring distribution uniformity and calibrating granular broadcast spreaders. It provides a uniform method to test, analyze and report performance data for spinner spreaders along with guidelines for test setup, collection devices, determination of application rates and effective swath width. The International Organization for Standardization (ISO) also describes standard testing procedures for calibrating fertilizer distributors (ISO 5690-1:1985 and ISO 5690-2:1984). These standards specify the test methods for distribution of solid fertilizers which includes primary tests for calibration, and test for determination of physical properties of fertilizers along with optional calibration tests. The Alabama Cooperative Extension System (ACES) published an article identifying a procedure for calibrating poultry litter spreaders (Mitchell and Tyson, 2001). They reported that several factors affect and should be monitored during calibration including: ground speed, power take off (PTO) speed, discharge opening, and swath width.

Mitchell and Tyson (2001) evaluated three methods of calibration. The first method required applying the known weight of litter uniformly over a field of known size. The second method utilized a tarp to cover a known portion of ground and then making three equally spaced passes over the tarp. The collected material was weighed, divided by the tarp area and converted to an application rate. The last method included setting rows of pans in the field and making three passes over them. Then the material collected in the pans was weighed with data plotted to evaluate material distribution and uniformity. The Virginia Cooperative Extension proposes using the tarp approach to determine uniformity and swath width rather than the pan method Marsh et al. (2003). They suggested using the same spreader settings after calibration to ensure the correct amount of applied litter.

Parish (1986) compared the spreader pattern evaluation methods using one spreader and two materials. They concluded that there can be significant differences in the apparent rate, optimum swath width, amount of skewing, and CV of the overlapped pattern resulting from the choice of collection methods. Traditional baffled pans produced a CV 8% to 22%, floor collection 21% to 41% and long narrow pans 27% to 57 %. Major differences were due to material bouncing out of the various collection devices. Additional work was needed to authoritatively state that one method is right and others wrong.

Pattern tests were conducted on three commercial fertilizer spreaders using two different products for comparing delivery rates by Parish (2000). The ASABE S341.3 standard (2004) was followed for all the test setups. Application rates were determined through pattern testing and calibration of the delivery system by collecting the material in a bucket without the distribution system. Results indicated that half of the comparisons between the rates determined by pattern based data versus rates calculated during conveying calibration were statistically different.

Application rates based on the pattern data were higher in most cases. The study confirmed that significant spreader delivery rate errors can be generated from pattern tests when conducted on a smooth surface. The author suggested that rate calibration should be conducted after an effective swath width was determined through pattern testing.

2.2.3 Distribution Patterns and Uniformity

Spinner spreaders rely on overlap from adjacent passes to achieve uniform distribution. The mean overall application rate and application uniformity depends on the overlap pattern of the material being applied. The amount of overlap depends on how far the spinner discs throw material and on the swath width, which is the distance from the centerline of travel of one pass of the spreader to the centerline of travel of the adjacent pass. Spinner-disc spreaders have a disadvantage of producing an uneven (poor) distribution of material (Figure 2.3a showing a typical simulated overlap pattern). Theoretically the ideal distribution pattern for a spinner-spreader is flat top pattern as shown in Figure 2.3(b). The distribution pattern of fertilizer products are dependent upon the type of spreader and hardware settings being utilized. Over the past several decades, various research attempts have been made to gain a better understanding of variables that affect the spread and uniformity of granular fertilizers using different types of applicators including spinner-disc spreaders. Most of these studies used inorganic fertilizers but knowledge can be gained from these investigations. Also, significant research has been conducted to determine the influence of machine parameters and material properties on pattern uniformity.

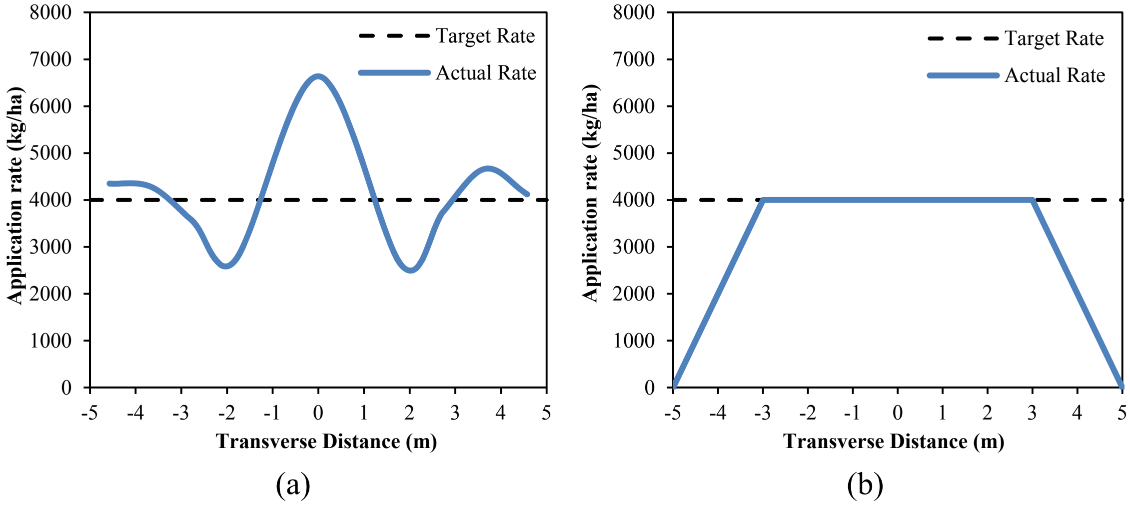


Figure 2.3. Figure illustrating a typical W shape (a) and perfect flat top (b) simulated overlap pattern for a spinner-disc spreader.

Knowledge of material properties is important when trying to evaluate the uniformity of distribution patterns. Hollmann (1962) examined the effects of particle size on spread patterns. A series of fertilizers with different particle sizes were tested. The experiments showed that the projected distance (spread width) increased by about 150% as the particle size increased from 0.3 to 3.0 mm. No significant difference was determined in spread patterns for particle sizes larger than 1.0 mm. Hoffmeister et al. (1964) also studied the effect of particle size of fertilizer materials on distribution patterns. The most common variables that affect spread uniformity are particle size, density and shape of the particles (Williams, 1976). A simulation study by Pitt et al. (1982) reported that the variation in particle size had only a slight effect on lateral distribution of particles by a spinning-disc spreader, although mean particle size had a major influence on the shape of the spread pattern. Hofstee and Huisman (1990) did a thorough review of the effect of particle size on spread patterns and concluded that particle size and distribution affected fertilizer distribution, but the influence on the spread pattern was difficult to establish. Additionally, they recommended that small particles caused a higher coefficient of variation (CV), thereby impacting uniformity and a smaller spread width. Hofstee (1995) studied the effect of physical properties of fertilizer on uniformity and concluded that the coefficient of friction was the most important physical property impacting particle motion on the vane surface. Several other researchers have reported that fertilizer granule size was the most important factor influencing distribution and uniformity (Bradley and Farnish, 2005; Bridle et al., 2004). Miserque et al. (2008) concluded that particle size and density are the major particle parameters affecting the spread pattern, with shape as a minimal influencing factor.

Beside material properties, machine parameters are also important factors affecting spreader performance. Glover and Baird (1973) evaluated distribution patterns for several spinning disc spreaders. It was observed in their tests that moving the flow divider or chute forward improved the spread patterns for both fertilizer and wet lime. The tests also indicated that the material flow chute (divider) must be adjusted for different application rates to eliminate extra peaks in the pattern.

Olieslagers et al. (1996) developed a simulation model for calculating fertilizer distribution patterns from a spinning disc spreader. Spreader patterns for single- and twin-disc spreaders were calculated by using this model. They reported that position and shape of the orifice along with changes in mass flow affects the pattern whereas change in the disc angular velocity strongly influences spread width. They suggested that the negative influence of changing only one parameter for maintaining desired mass flow should be avoided by adapting/changing other controllable parameters. Further validation was needed to examine the effectiveness of the model for different spreader settings and particle characteristics.

The effect of impeller angle on pattern uniformity was determined by Parish (2003) using a walk-behind spreader. Even at small angles (5 degree - corresponds to a handle height change of 3.8 to 6.4 cm), the changes in the pattern were significant. Author suggested the need for bubble leveler or electronic out-of-level warning system using mercury switches. The effect of vane height on distribution uniformity in rotary fertilizer spreaders with different flow rates for triple superphosphate (TSP) and calcium ammonium nitrate (CAN) was investigated by Yildirim and Kara (2003). They used vane heights of 25, 35, 45, 55 and 65 mm along with orifice diameters of 30, 35, 40 and 45 mm. The vane length and impeller diameter used were 120 mm and 500 mm, respectively. The most uniform distribution was obtained for a vane height of 35 mm and orifice diameter of 35 mm for both fertilizers. For TSP, mean CV's ranged from 7% to 20% while a range of 6% to 17 % was measured for CAN of different combinations for vane height and orifice diameter.

Yildirim (2006) showed the impact of disc cone angle and revolution speed on fertilizer distribution uniformity. He conducted the tests on single-disc rotary fertilizer spreaders with different flow rates using triple superphosphate. The cone angles of the discs used in the experiment were 0, 10 and 20 degree with disc speeds of 405, 540 and 810 rpm. The best distribution Uniformity was achieved at a combination of disc cone angle equal to 0 degree, disc speed of 820 rpm and orifice diameter of 30 mm. Distribution uniformity became worse as the cone angle of disc increased and became better as the disc speed increased with all orifice diameters (30, 40 and 50 mm).

Yildirim (2007 and 2008) also studied the effect of vane number and different vane shapes on the distribution uniformity in single–disc rotary fertilizer spreaders with different flow rates using TSP and CAN. The number of vanes tested was 2, 4, 6, 8, 10 and 12 and vane shapes characterized as straight, composite, forward–curved–5, forward–curved–10, back–curved–5 and back–curved–10. The orifices of 30, 40 and 50 mm diameters were used at the bottom of the hopper to obtain the different fertilizer flow rates. The data (2007) showed that the best distribution for both fertilizers was obtained with the combination of two vanes and an orifice diameter of 30 mm. The values of CV obtained from all the combinations between the vane number and orifice diameter varied between 11% and 34% for TSP, and 10% and 35% for CAN. As the vane number increased from 2 to 12, the CV's increased for all flow rates. The study on different vane shapes showed that the shape of vane had a significant effect on fertilizer distribution uniformity. The best fertilizer distribution uniformity was obtained from the forward curved–5 vane shape, not the straight vane shape, for both TSP and CAN.

Many new technologies (feedback control, optical sensors, etc.) and effect of wind speed and direction along with other climatic parameters have been also tested to examine spread uniformity of fertilizers. Application uniformity with fertilizer applied under cross wind applications was found to be worse than applied into a head wind (Smith et al., 2004). Smith et al. (2004) studied the effect of wind speed, wind direction, fertilizer material and swath spacing on the uniformity of granular fertilizer applications with a spinner truck. Results showed that up down and racetrack application patterns were equally effective with respect to the uniformity of the applied granular materials. Ammonium nitrate exhibited CV's of less than 15% with low wind speeds, cross winds and a swath width less than 10 m. Only 12% of the CV's were less than 15%. Average pan recoveries for potash, 13-13-13 and ammonium nitrate were found to be 95.5%, 78.9% and 54.4 %, respectively. They also recommended that pan recovery data should be used to calibrate a spreader.

A sensor was developed to determine the real-time prediction of the spread pattern by Grift and Hofstee (2002). Results showed that the sensor produced an excellent indication of fertilizer dispersion behind the spreader but further validation was needed using the ASABE

S341.3 (2004) testing standards. Kweon and Grift (2006) simulated the spread patterns by feed gate adaption method (use of optical sensor and control algorithm) and acceptable patterns were produced at any application rate but authors stated the need for field testing for validating the simulations.

Fulton et al. (2005) investigated distribution patterns at varying rates for different granular applicators using two spinner spreaders (A and B) and two pneumatic spreaders (C and D). Results showed a triangular pattern for spinner spreader B with consistent patterns for the pneumatic applicators. Applicator's B and C generated CV's greater than 20%. Applicator A performed well at lower rates (CV=19%) but not at higher rates whereas applicator D generated CV's between 25% and 34%. Results concluded that spinner-disc spreaders over applied while pneumatic applicators under applied at the pattern margins suggesting an adjustment to the effective swath width. Overlap plots indicated pattern variability even when CV's were acceptable for B and C. Pattern shifts were observed for applicator A. They suggested the need for proper calibration to maintain acceptable performance but also a VRT equipment testing standard.

2.2.4 Uneven Fertilizer Distribution

Fertilizers are applied to fields to attain desired soil fertility levels. Uneven distribution of fertilizers creates variable fertility levels within a field possibly impacting crop yields. Jensen and Pesek (1962a, 1962b) developed a theoretical model that quantified yield loss expected from non-uniform distribution across the swath width of bulk spreaders. Their model predicted that the greatest loss of corn production would be from fields with very low fertility level. Field data analysis indicated that the magnitude of loss was 0.78, 0.27 and 0.04 Mg/ha of corn on soils of very low, low and medium, respectively.

Welch et al. (1964) studied nutrient responses to estimate the effects of non-uniform, blended fertilizer applications on corn and bermudagrass. In an example of non-uniformity involving coastal bermudagrass, they reported that 40% of the area received twice the desired fertilizer rate, 40% received the half as much, and only 20% received the correct amount. They found that total yields under non-uniform conditions decreased by only 3% as compared to yield under uniform application. Dumenil and Benson (1973) analyzed the effects of non-fertilizer application on corn yields. They pointed out that corn yield losses due to non-uniform fertilizer distribution can vary from none to considerable and are mainly influenced by (1) fertilizer distribution patterns over the width and along the path of the swath, (2) yield response to the nutrients applied, and (3) nutrient rates applied. They estimated yield reductions for corn from several shapes of non-uniform fertilizer application patterns and found that the magnitude of loss across the swath vary primarily due to degree of non-uniformity and nature of the response curve. They estimated that yield loss would increase four fold for every double deviation from the desired rate.

Lutz et al. (1975) studied the effect of uneven spreading of lime on soil pH and yield of rotation crops. The study investigated five different spread patterns, including those obtained with bulk spreaders used in normal farming operations. Results indicated that lime spread patterns did not significantly affect the yields of corn, barley and soybeans grown on a silt loam, in Blacksburg, VA., whereas yields of soybeans and corn grown on a Norfolk sandy loam, at Capron, VA., were affected by the lime spread patterns. The reduction in yields was due to zinc deficiency in the plants because of non-uniform application of lime. They also reported that soil pH increased with increase in rate of lime applied. Sogaard and Kierkegaard (1994) evaluated yield reduction resulting from uneven fertilizer distribution in grain crops. They concluded that a spatial distribution coefficient of variation less than 20% was necessary to minimize loss of net profit. The authors suggested that future research should focus more on the development of centrifugal spreaders by improving the abilities of the fertilizer spreaders under realistic field conditions. It should be noted that these studies were conducted with spinner spreaders that were applying at smaller swath widths (12.2 to 18.3 m) in comparison to today's spreaders with common recommended widths between 18.3 and 30.5 m.

Spreading issues can occur with both lime and fertilizer materials within farm fields for all kinds of spreaders including spinner-disc spreaders. The Maryland Cooperative Extension (Stewart and Bandel, 2002) listed some important steps to reduce non-uniform distribution of lime and fertilizer in the fields. The most important step was evaluation of distribution patterns produced by the spreader under normal operating conditions. Field testing, using the actual fertilizer to be applied and right application rate along with other spreader settings (gears and ground speed), was recommended for evaluating spreader distribution patterns. It was also suggested that operators must understand the factors that affect the distribution patterns and other equipment adjustments in order to achieve the best possible results related to fertilizer and lime application.

Yule and Lawrence (2007) developed a methodology for measuring and evaluating the true agronomic and economic consequences of uneven fertilizer spreading from a broadcast fertilizer. The method requires the following parameters to be used in the application model: the creation of "as-applied" fertilizer surfaces within GIS software, the extraction of application statistics, calculation of respective crop responses to the fertilizer input, and calculation of the economic value of applying the fertilizer used. Economic analysis results showed that current spreading methods would result in significant economic losses (NZ$66.18 per ha) for dairy system. Farm data indicated that a typical dairy farm in New Zealand would loose between $52 and $72 /ha/yr) due to inaccurate fertilizer application. The authors suggested the need for improvement in the fertilizer application process and use of new technologies to reduce the economic losses due to inaccurate and uneven fertilizer application.

2.2.5 LITTER SPREADERS

Limited amount of research is conducted for investigating distribution of litter using spinner-disc spreaders. Wilhoit et al. (1993) evaluated the distribution pattern of poultry litter using a centrifugal-type broadcasting spreader along with studying the effect of particle size on nutrient distribution across the swath. A pull-type spreader with a ground-driven, 41-cm wide bed chain, and two 61-cm diameter, six-blade spinners was used in this study. The poultry litter used in this test was mixed pine shaving and peanut hull litter that had been used for growing six flocks of birds. The moisture content of the litter averaged 29% dry basis. Results illustrated that smaller particles tended to land directly behind the spreader with larger particles being distributed further out. Nutrient analysis showed that both C and N concentrations were uniform across the swath with little variations between particle size and nutrient content. The best uniformity was obtained with a simulated travel spacing of 8.5 m. The swath width recommended by manufacturers was not found to be the optimum with the authors suggesting smaller swath widths applying poultry litter.

A drop applicator was developed and evaluated for applying poultry litter in a uniform swath at controlled rates (Wilhoit et al., 1994). The applicator consisted of floor chain arrangement to meter out poultry litter from the bottom of the hopper over a 1.7–m width. The results showed that litter application rate was not affected by the depth in the hopper. Calibration was primarily volume-based and, therefore, dependent on chain speed, for both individual chain flights and mesh chain floor arrangements. The tests indicated that the litter was applied with fairly good uniformity across the swath but the application rate fluctuated cyclically in the direction of travel when the floor chain with individual chain flights was used. The mesh chain eliminated the cyclic fluctuations providing good uniformity in the direction of travel.

The physical properties of poultry litter are more variable than inorganic fertilizers; therefore tend to have more effect on distribution. Thirion et al. (1998) investigated the influence of physical characteristics of different animal manures including poultry litter, on spreader performance. They used 2 types of litter with the same spreader and adjustments to evaluate the effect of manure heterogeneity on working of spreader deposition. The two types of litter used were: a more heterogeneous load (49% variability) and a less heterogeneous (9% variability). They reported that less heterogeneous manure produced a good quality of spread (CV=8%) whereas more heterogeneous manure produced a low quality of spread (CV=29%). They suggested that it was very important to verify the heterogeneity of manure when planning to assess spreader performance.

A study was conducted by Pezzi and Rondelli (2002) on a prototype spreader for evaluation of the distribution of four poultry manures differing in composting degree and moisture content. The chemical and physical properties such as wet bulk density, moisture content and static frictional characteristics of the manures were measured. The prototype was set up for orchard and arable crops. The spinner disc speed and point of delivery of the organic fertilizers onto the spinners were adjusted to broadcast manure as well for distribution in bands. In the former, an increase in spinner disc speed improved the throwing width and effective swath width. They found that the best results for the point of delivery of organic material were achieved by moving the point of delivery away from the center of the spinners. Also for band distribution, the best results were observed when the point of delivery coincided with the center of the spinners with a low spinner disc speed. The physical properties of the fertilizers influenced the distribution pattern with poorest results being the distribution of manure with large particles at high moisture content.

Campbell et al. (2008) evaluated the improvement of poultry litter with spinner spreaders. A litter spreader with electronically adjustable hydraulic flow control valve (closed loop system CLS) and a traditional manual valve (open loop system, OLS) was used with three application rates (2240, 4480, and 6720 kg/ha). Results indicated that CLS generated low CV's than OLS but manual valve provided more symmetrical and consistent patterns. CLS system maintained more constant spinner speeds resulting in more uniform overlap patterns generating lower CV's. Campbell et al. (2010) also conducted a study to evaluate whether macronutrient (N, P_2O_5 and K_2O) distribution patterns contrast with the traditional mass distribution. He used three application rates (2242, 4483 and 6725 kg/ha) for applying broiler litter. A two dimensional collection pan matrix with four rows was used to assess pattern uniformity. Results indicated that even with the existence of particle size variability across the spread patterns, the distribution of mass reflected the nutrient distribution. The CLS provided more uniform nutrient patterns, with CV's ranging from 22% to 34% compared to the 26% to 39% generated by the OLS. This research concluded that the distribution of mass can be used to assess nutrient distribution of poultry litter by spinner spreaders and the CLS for spinner-disc speed control outperformed the traditional OLS.

2.3 Rate Controllers And Variable-rate Technology

Rate controllers are starting to be used more frequently on spreaders for better control and management of product in the field. They provide several benefits including easier calibration of equipment and improved application efficiency. Figure 2.3 shows one of the rate controllers (Topcon Precision Ag X20) commonly used on spinner spreaders. These controllers have various setup menu options which are used to enter product properties and spreader parameters prior to any calibration or application. The setup menus usually requires manual entering of parameters such as gate height, swath width, and product density along with feedback from tractor GPS for ground speed to maintain the target application rate. The controllers are loaded with spreader control software program which provides both variable rate application and spinner-disc speed control capabilities. The speed control for conveyor chain and spinner-discs is maintained by using electronically adjustable hydraulic valves. The spreader control software also receives continuous speed feedback from spinner-disc and conveyor chain sensors during spreader operation to maintain the desired speeds.

Figure 2.3. Example of a display-rate controller (Topcon Precision Ag X20) commonly used for spinner-disc spreaders.

Rate controller when used with a GPS, guidance system and field boundary map can be utilized for performing variable-rate (VR) application of product. Variable-rate technology (VRT) provides a tool to reduce the over-application of nutrients by spatially applying the proper amount to meet local fertility needs. Various studies have been conducted to determine the affect of VRT on fertilizer application. Most of these studies have used granular fertilizers with limited literature available about using VRT for applying poultry litter. Developing a prescription map is the most important component of VRT application (Sawyer, 1994 and Ferguson et al., 1996). Fleming and Westfall (2000) suggested that ground-testing (soil testing) along with past experience must be used to develop accurate VRT maps based on management zones. Fulton et al. (2001) suggested modifications to the ASABE Standard 341.2 (ASABE standards, 2009) to include a 2-D array of collection pans to asses variable-rate application (VRA) of granular products. It is assumed that if VRT can improve the application of inorganic fertilizers then it can be utilized to improve litter application.

The effect of using VRT of an input following a treatment map as well as using yield monitoring to measure the crop's response was studied by Lark and Wheeler (2003). They reported that this technology could help farmers get the maximum economic yields out of their fields. Chan et al. (2002) pointed out that the accuracy of VRA depends on the accuracy of the GPS data utilized for mapping the fields.

Knowing the response time of a variable-rate system is a key during field application to minimize application errors. Molin et al. (2002) tested a spreader with VRT for granular fertilizer with three swath widths (18, 21, and 24 m) and three rates (50,150, and 250 kg/ha). They used 70-m longitudinal line of collectors on both sides of the machine with total length divided into 3 parts. Results illustrated that the response time for rate changes for a decreasing step was more than an increasing step. Variation of the application rate on steps of 50 and 100 kg/ha did not cause any variation on the response time. The effective swath width of 24 m was not affected by application rate change provided the best uniformity with CV's under 15%. Flow rates obtained during the tests showed to be consistently lower than those programmed.

The dynamics of an applicator can have important performance effects. Schueller (1994) discussed the concepts of spatially variable fertilizer and pesticide application with GPS and DGPS. He showed that Command feed forward control can significantly improve the performance in application of fertilizers but the various error sources can degrade the performance of spatially-variable applicators. However, further research was needed on understanding the effects of the various error sources. Fulton et al. (2003) concluded that prescription maps do not always reflect actual application and can sometimes generate misleading results due to application errors. Therefore, variable-rate application (VRA) could be a viable option for managing nutrient inputs, but there can be various application errors associated with both prescription maps and VRT equipment. Fulton et al. (2005) also demonstrated potential application errors with VRT and suggested the need for proper calibration for acceptable performance.

Lawrence and Yule (2005) evaluated spreader performance for variable-rate fertilizer application using different spreading testing protocols. A spreader truck with dual spinners operating at 750 rpm and application rates of 80, 100, and 150 kg/ha was tested. The coefficient of variation (CV) was used for compare the different testing methods with a CV of 15% being considered acceptable uniformity. They concluded that overlap spread pattern was a major limiting factor of accurately applying fertilizer in the correct application zone. The spreader on average over-applied the attempted rate in all three application zones. They also showed, out of different methods using tray testing system, using fewer trays also provided similar results.

Fulton et al. (2001) assessed the performance of a variable rate spinner disc fertilizer applicator and outlined development of an as-applied model to represent material distribution. A Sigmoidal function described increasing application rate changes while a linear function characterized decreasing rate changes. Uniform and VR applications were mathematically modeled. The test showed that the modeled rate change did a good job of projecting the actual distribution. Comparison between the distribution patterns showed that there could be a need to adjust the spreader hardware to maintain a uniform pattern during VRA. The need for adjusting the fins and concurrent movement of the rear divider during rate changes might improve pattern uniformity as suggested by authors.

2.4 Moisture Measurement Techniques

Moisture content in bio-materials is an important decision variable during harvesting, storage, transportation and other processing operations. Several studies have shown the effect of litter moisture content on other physical properties such as bulk density, and of these properties on spreader performance. Moisture content in commonly available litter can vary between 15% to 40% wet basis depending on the type of management practice (Lague et al, 2005). This variation can affect spreader performance impacting litter application. Therefore, accurate determination of litter moisture before and while spreading can be used to reduce application errors and more precisely control the rate on-the-go. Standard and reference methods for determining moisture content involve tedious laboratory procedures and long oven-drying periods. Therefore, rapid methods for moisture measurement is essential for predicting the real-time moisture content and providing rapid information for site-specific decision making related to litter application. Limited research using any real-time moisture sensing devices has been conducted on litter moisture measurement. The challenge is to find a suitable sensor that will be able to provide reasonable MC estimates on a real-time basis during conveyance of litter.

2.4.1 Contact Techniques

Contact method of moisture sensing involves a sensor in contact with the material during measurement. This approach is also known as intrusive type of moisture measurement. This technique usually involves sensing a resistance or/and capacitance change for the sample between the electrodes, thus sensing the dielectric properties of the material. The dielectric properties of biomaterials have been mainly used for moisture measurement because of their useful for rapid moisture content sensing. The low cost and simple working principle of contact sensors supports their continuous use for moisture measurement in different biomaterials such as corn, hay etc.

2.4.1.1 Resistive and Capacitive

Moisture meters based on electric resistance or capacitance type are the most common instruments for determining moisture content in biomaterials. Within a limit, these sensors are able to provide precise information about moisture content in agricultural materials. Kandala et al. (1987) used a small parallel-plate capacitive sensor for measuring kernel moisture content in corn. The capacitance was measured at a frequency of 1 MHz with and without the kernel in place. They reported that kernel moisture content was predicted within ±1% moisture over a 12% to 20% moisture range with 80% reliability at most moisture levels. A predictive model was developed by Chung and Verma (1991) for continuous measurement of rice moisture content during drying using resistance-type sensors. The effects of grain pressure, sensor orientation, moisture content and temperature on the moisture sensor output were investigated. They found that simple resistive type sensors could provide a good estimate of MC within ±1%. Grain temperature was a more useful factor than local air temperature in the predictive model.

Various moisture measurement sensors were reviewed by Marcotte et al. (1999) for measuring moisture during hay and forage harvest. They suggested that capacitive type sensors would be most suitable to estimate moisture in pneumatic conveying while impedance or conductivity type sensors might be more appropriate in balers. Osman et al. (2001 and 2003) classified moisture measurement systems as direct or indirect methods. They also developed and evaluated a parallel-plate capacitor type moisture sensor for measuring hay moisture content and concluded that this type of sensor could not directly estimate moisture content (%) but a good correlation was observed between the sensor's output and the amount of moisture in hay.

Mendes et al. (2008) evaluated and calibrated a soil moisture sensor for measuring moisture content in different types of poultry manures. Four EC-5 capacitance-type sensors were used for measuring MC of meat-bird (broiler and turkey) litters and laying-hen manure. The sensors were immersed into plastic vessels containing poultry litter/manure and a CR10 measurement and control module was used for programming and data retrieving. Tests were conducted under environmentally controlled laboratory conditions. Data showed that MC varied from 27.1% to 55% for the broiler litter, 22.8% to 56.1% for the turkey litter, and 11.0% to 75.0% for layer manure. Bulk density varied from 318 to 468 kg/m^3 for the meat-bird litters. The sensitivity of the sensor to the source temperature was also evaluated and it was found that the impact of litter temperature on MC measurement by the sensor was rather small. Results of the study indicated that when properly calibrated, the soil moisture measurement sensor can be used to quantify moisture content of poultry litter on a real-time basis.

Moisture content in compacted hay during drying was monitored by Savoie et al. (2011) using two moisture probes based on electrical resistance. A thermocouple was also inserted in individual layers of hay of 135-mm thickness. The probe MC measurements were compared with those obtained through oven drying. The probe measurements illustrated that the MC of hay decreased over time, and also faster drying for layers closer to the heated air flow. The probe MC needed to be corrected with a linear regression model to improve its prediction. Results indicated that dynamic and continuous measurement of MC during forage drying was feasible with a relatively low-cost resistive type sensor but further validation within different operating environments was needed.

2.4.2 Non-contact Techniques

In some cases, the type of operating environment and material does not permit the direct sensor contact with material being sensed. A different, non-contact approach for moisture measurement using extrusive devices is used in these types of situations. These devices measures specific material properties (mostly optical) from a certain distance depending on type of sensing principle and the amount of accuracy desired in the measurement. The measured properties are used for determining the actual moisture content in the material. Infrared (IR), near infrared (NIR), microwave and neutron techniques are some commonly used non-contact moisture measurement techniques. In the past, researchers have successfully used these techniques for rapid moisture sensing in biomaterials such as cotton, hay, forage etc. and have also provided valuable information for incorporating these techniques on agricultural equipment for better material handling and process control.

2.4.2.1 INFRARED AND NEAR-INFRARED

The use of surface reflectance measurements utilizing certain wavelengths has increased significantly in the past decade, particularly in biological materials. One such technique is infrared spectroscopy, which utilizes infrared region of the electromagnetic region to measure material reflectance and absorbance properties. Moisture information for the material can be easily extracted from the spectra by examining material reflectance properties at certain wavelengths. Infrared sensors have been successfully used by researchers for moisture measurements in biomaterials and reported to work quite well. Anthony and Griffin (1984, 1986) evaluated an infrared-type sensor for measuring the moisture content of ginned lint and its possible use in control systems for gin. They used a non-contact, infrared-type of moisture meter, with emitter and receptor located on the same side of the target, in this study. The sensor was installed at the feed control of the microgin and the feed control hopper provided cotton at a depth of about 1 m above the sensor. The moisture meter measured the moisture content of lint cotton during continuous gin processing. The response of the instrument to change in lint moisture was analyzed by fitting a regression line. The device measured the lint moisture to the nearest 0.5 percentage point with coefficient of determination of 0.96. Results indicated that the meter accurately predicted lint moisture in the seed cotton and has potential for incorporation into a moisture control system for gins.

Near-Infrared (NIR) spectroscopy for moisture measurement gained interest because of its convenient and relatively large volume sampling. NIR characterizes the material based on its absorption in the 4000 – 12,500 cm^{-1} wavelength region, utilizing much broader features than IR spectra. NIR spectroscopy is well suited for measurement of moisture, since water O-H group overtone and combination bands are pronounced in this region in the spectrum. This technique is readily adaptable and the low intensities of NIR absorptions permit the direct measurement of water over wide ranges in samples. NIR spectroscopy has been also used for analysis of poultry or animal manures by few researchers (Reeves, 2001; Reeves et al, 2002 and Sorensen et al, 2007). Reeves (2001) evaluated near-infrared reflectance spectroscopy (NIRS) for determining the composition of poultry manures and its feasibility and limitations for analyzing poultry manures. A commercial testing laboratory provided manure samples and conventionally determined analyte values for total N, $NH4^+$-N, organic N, minerals and moisture in the samples. The moisture content of the manures used for study ranged from a minimum of 12% to a maximum of 65.1%. Samples were blended using a food blender before any analysis. Spectra's from 400 – 2498 nm were obtained using NIR Systems model 6500 monochromator with data collected every 2 nm interval at a bandwidth of 10 nm. Results indicated that scanning more number of samples by using more replicates would likely to improve calibrations. For a comparison of full spectra results (400 – 2498 nm) to those achieved using NIR region (1100–2498 nm), it was found that the NIR data was able to predict the moisture and $NH4^+$-N alone versus using the full spectra. Overall results for NIRS on poultry manures showed that accurate calibrations for ammonium, organic and total N and moisture content can be developed using NIR spectra with coefficient of determination (R^2) of 0.725, 0.894, 0.886 and 0.843, respectively. Determination of minerals in manures was not viable using any of the spectral regions. Reeves et al. (2002) verified that ammonia could be determined with reasonable accuracy by NIRS using 1100 to 2498 nm spectral range with final calibration R^2 of 0.90.

Ye et al. (2005) conducted NIRS to analyze nutrients in different manures (111 solid poultry layer, 95 solid poultry broiler litter, 39 swine solid hoop and 85 swine slurry). The total solids (TS) in manures ranged between 26.49% and 88.49%. The R^2 values for TS, total nitrogen and NH_3-N were between 0.80 and 0.97 for all manures. Authors concluded that NIRS can be effectively used for determining nutrient composition and certain minerals in manures. Soronsen et al. (2007) also investigated the feasibility of using NIRS for rapid determination of the composition of cattle and pig slurries. Samples with total solids content from <1 to 15% were collected during a 3-yr period and used for calibration and validation. Spectral data in the range 1200 – 2400 nm were used for calibration based on partial least squares regression. Final results indicated that dry matter (DM), N, NH_4-N and P can be determined with R^2 values of 0.97, 0.94, 0.92 and 0.87, respectively. They concluded that NIRS methodology is suitable for rapid analysis of DM, C, N, NH4-N, and P in both cattle and pig manures.

2.4.2.2 MICROWAVE

Currently, moisture measurement using microwave frequencies are of interest in grain and seeds only. Early work on sensing moisture content in grain by microwave measurements was initiated by Kraszewski and Kullinski (1976), who examined the attenuation and phase shift of waves traversing a grain layer. The ratio of attenuation and phase shift was investigated as a density-independent function for microwave sensing of moisture content (Jacobsen et al., 1980; Kent and Meyer, 1982; Kress-Rogers and Kent, 1987). Further studies with microwave measurements confirmed the usefulness of this ratio for sensing moisture content independent of bulk density fluctuations in grains and indicated a possibility of a single calibration for several materials (Kraszewski, 1988; Nelson and Kraszewski, 1990).

Mclendon et al. (1993) conducted density independent measurement of moisture content in static and flowing grain using microwave frequencies. During static testing, microwave measurements were taken on wheat confined in a sample holder located between two antennas whereas continuous moisture measurements were taken of a stream of flowing grain discharged from a storage bin for dynamic testing. Data indicated that moisture measurements were predicted within ±0.7% for the static samples and within ±1.2% for wheat in a dynamic, solid-flow condition. Density-independent moisture measurements can be made on wheat within a specific density range (0.72 to 0.81 g/cm^3).

A low-cost microwave sensor was built and tested Trabelsi et al. (2007) for nondestructive, rapid sensing of moisture content in granular and particulate materials. The sensor was based on the principle of free-space transmission for moisture determination from measurement of the dielectric properties of the material. Results for wheat and soybeans showed that moisture content can be determined in either material from a single moisture calibration equation with a standard error of 0.5%. They proposed that this sensor can provide widespread integration of microwave sensing technology in dealing with granular and particulate materials, including food and agriculture, mining and construction. Nelson and Trabelsi (2010) showed that grain and seed permittivity's can be measured at microwave frequencies for rapid sensing of moisture content. They also supported the idea of a universal calibration, which would provide a significant advantage and should encourage the development of microwave moisture sensors for on-line applications for grain and other biomaterials in agriculture industry.

2.5 Summary

The environmental concerns due to litter over-application have led to its more efficient management. This efficiency can be achieved by improving technology on a litter spreader for increasing spread accuracy and uniformity. Studies have shown the effect of litter properties and spreader parameters on spreader performance and thereby distribution in the field. However, the high variability in litter physical properties, especially moisture content and bulk density, makes it more difficult to maintain acceptable application in the field. The solution to this problem requires determination and accounting for the litter moisture or/and density variations in a spreader rate controller. Researchers have evaluated both contact and non-contact type moisture measurement techniques for moisture determination in various biomaterials including poultry litter. Based on past research, capacitive and near infrared spectroscopy (NIRS) methods appeared to be feasible options for inline moisture measurement in poultry litter. Further research was needed to evaluate the feasibility of these methods for real-time moisture measurement in litter on a spinner-disc spreader.

CHAPTER THREE

INFLUENCE OF BROILER LITTER BULK DENSITY ON FIELD APPLICATION WITH A SPINNER-DISC SPREADER

3.1 Abstract

Poultry litter is commonly land applied as an organic fertilizer on crop and pasture land. However, the high variability in physical characteristics of litter, especially moisture content and bulk density makes it difficult to maintain accurate metering and uniform distribution during application with spinner-disc spreaders. A study was conducted to understand the effect of litter bulk density on conveyor metering and spread distribution for a spinner-disc, litter spreader. Two loads of broiler litter (A and B) at two different moisture contents (32% and 28%, respectively) and wet bulk densities (416.5 and 480.6 kg/m^3, respectively) were used in this study. Different spreader and rate controller settings (two gate heights: 17.8 and 34.9 cm, four application rates: 1743, 3424, 3486 and 6848 kg/ha, two correct (actual) density values: 416.5 and 480.6 kg/m^3, and three incorrect (virtual) density values: 352.4, 416.5 and 544.6 kg/m^3) were established as treatments. Results indicated that incorrect density treatments generated high discharge rate errors (>±15%) during conveyance tests. Field application rates were also outside the considered 10% acceptable limits for both litter types (A & B). The central peak of the single-pass patterns at different density treatments varied with actual application rate (mass flow). Standardized patterns at different density treatments for the same litter type were found to be statistically different ($p<0.05$) at a few transverse positions across the swath. These results indicated the

importance of determining and using the correct density value within a spreader, rate controller for accurate application with spinner-disc spreaders.

3.2 INTRODUCTION

The escalating prices of inorganic fertilizers have made litter an attractable and alternative fertilizer source. In many southeastern states, litter has been used as a fertilizer by applying it to crop and pasture lands to meet soil or plant nutrient requirements due to its high nutritive value and availability in some regions. Poultry production in Alabama generates approximately 2 million tons of poultry litter annually (Mitchell and Tyson, 2007). In the past, litter has been applied near production facilities. Continued application in these areas over the years has resulted in increased environmental concerns due to off-site transport of nutrients; specifically nitrogen (N) and phosphorus (P). These environmental issues associated with litter application have initiated the need to enhance environmental and nutrient stewardship at the farm level. Most of the current research focuses on best management practices (BPMs) for litter including means to improve field application. The 4R's of nutrient management (Right rate, Right time, Right place and Right source) are being promoted by the fertilizer industry and agencies such as USDA-NRCS to ensure accurate metering and placement of materials while reducing environmental risks. The 4R's concept along with recent precision agriculture technologies such as variable-rate (VR) also provides the basis to improve litter spreading thereby reducing the risk of offsite nutrient transport. However, poultry litter is extremely variable in terms of its physical characteristics such as particle size, bulk density, compressibility (Bernhart et al., 2009) and moisture content (Ndegwa et al., 1991; Malone et al., 1992). This inherent variability makes it difficult to uniformly and accurately apply litter using spinner-disc spreaders (Thirion et al., 1998; Lague et al., 2005).

Research has been conducted to investigate various physical properties of poultry litter. Biomaterials such as poultry litter are hygroscopic in nature and will therefore exchange moisture with their surroundings. Several studies have reported the effect of moisture content on physical properties of biological materials. Malone et al. (1992) reported that the wet bulk density and moisture content of clean-out manure, on average, increased from 432 kg/m^3 to 545 kg/m^3 and 27% to 32%, respectively as the number of flocks increased from a low of 1 to 6 to a high of 13 to 18 flocks, respectively. The dependence of moisture content on number of flocks raised on the litter was also emphasized by Jenkins (1989) and Wilhoit et al. (1993). Koon et al. (1992) determined low moisture content of 17.4% after the first week of growout to a high of 22.5% after the seventh flock for poultry litter with pine shavings.

Glancey and Hoffman (1996) reported that moisture content significantly increased the static coefficient of friction and wet bulk density of poultry litter. Thirion et al. (1998) investigated the physical properties of 25 different types of animal manures including poultry litter. They found that dry matter content for most of the manures ranged from 16% to 53% with bulk densities measured from a large variety of origins (animals, housing, etc.) varying significantly within the same batch and primarily depended on dry matter content. The variation in litter density as moisture content changes was also reported by Landry et al. (2004) and Lague et al. (2005). The heterogeneous nature of poultry litter and non-uniform loading conditions of spreaders makes it difficult to continuously monitor the rate of manure flow onto application equipment. Therefore, these researchers recommended the need for technology development to continuously sense and monitor manure nutrient content and flow rate for land application equipment (e.g. litter spreaders). Bernhart et al. (2009) indicated that increasing poultry litter moisture content resulted in a decrease in poured bulk density, particle density and porosity. The percent compressibility of poultry litter was reported to increase from 2.5% to 18.0% as sample moisture contents increased from 10.2% to 30.9%, respectively.

Knowledge of litter properties is also important when trying to evaluate the uniformity of spread. Wilhoit et al. (1993) reported that smaller particles tended to land directly behind a litter spreader with larger particles being distributed further out. The influence of litter heterogeneity on spreader performance was investigated by Thirion et al. (1998). A good quality of spread (CV = 8%) was obtained with a homogeneous material (9% variability) whereas a heterogeneous material (49% variability) produced low quality spreads (CV = 29%). Therefore, it is important to verify the heterogeneity of manure when planning to assess spreader performance. Pezzi and Rondelli (2002) evaluated a prototype spreader for applying four poultry manures differing in composting degree and moisture content. Improved distribution was found at high spinner speeds with a drop point away from the center of the spinner-discs. The physical properties of the manures influenced the distribution pattern with the worst distribution occurring with large particles at high moisture contents.

A key goal when applying organic and inorganic fertilizers with spinner-disc spreaders is to maintain spread uniformity along with accuracy for the target rate. Past research (Thirion et al., 1998; Landry et al., 2003; Lague et al., 2005) suggested that physical properties of applied materials in conjunction with machine parameters can have a significant effect on material distribution when applying with spinner-disc spreaders. Among these properties, moisture content and bulk density have a considerable amount of effect on application rates. There exists a considerable amount of research on understanding the machine parameters that can influence spread uniformity of spinner-disc spreaders including those equipped with recent technologies such as variable-rate technology (VRT) (Fulton et al., 2001; Molin et al., 2002; Lawrence and

Yule, 2005). However, limited information is available on the effect of litter physical properties, especially moisture content and bulk density, on accuracy and uniformity of spread. Knowing the moisture and bulk density of litter is important for application with a spinner-disc spreader since density is one of the required setup parameters for a rate controller including those with variable-rate capabilities. However, moisture content for commonly available poultry litter can vary between 15% and 40% (w.b.) depending upon the feeding and manure management systems (Lague et al., 2005). This large range in moisture content can cause a significant density variation within a batch ultimately impacting the amount of litter applied and possibly uniformity during field application.

The overall goal of this research is to develop technology to enhance litter application (i.e. metering and distribution) when using spinner-disc spreaders. We want to further the idea that real-time density updates within a spreader rate controller could help in better management of litter application.

3.3 Sub-Objectives

The specific objectives of this study were to (1) evaluate the effect of litter bulk density on conveyor discharge rate (mass flow) for a spinner-disc spreader, and (2) determine the impact of bulk density on distribution obtained from a litter spreader.

3.4 Materials and Methods

3.4.1 Equipment and Experimental Design

A standard litter spreader manufactured by Chandler Equipment Company (Gainesville, GA) was used for this investigation. This pull-type spreader was equipped with hydraulically controlled apron chain and dual rear spinner-discs. Each disc had four uniformly spaced vanes. Hydraulic flow control for the conveyor chain and spinner-discs was maintained using proportional valves (Brand Hydraulics, Omaha, NE) with pulse-width modulation (PWM) regulation. A John Deere 6420 tractor was used to pull the spreader during testing. The tractor was equipped with a John Deere GreenStar^{TM} AutoTrac^{TM} system using real-time kinematic (RTK) correction. A Topcon Precision Ag (Livermore, CA) X20 console loaded with Topcon's Spreader Control software and the corresponding electronic control unit (ECU) was used for apron chain and spinner-disc speed control. The X20 spreader setup menus required parameters such as gate height, swath width, and product density along with feedback from tractor GPS for ground speed to maintain the target application rate. A Proximity sensor (Automation Direct, Cumming, GA) mounted under one of the spinner-discs and a Dickey-John Encoder (Dickey-John Corp., Auburn, IL) coupled directly to the front shaft of the apron chain were used to monitor and control spinner disc speed and conveyor shaft speed, respectively.

Two types of broiler litter (termed as litter A and litter B) acquired from different production houses were selected. Bulk samples for both litters were collected randomly from the piles in sealed plastic bags and labeled accordingly. Mean moisture content and wet bulk density was determined for each type of litter before testing. A small load from bulk litter A was weighed and secured separately in a plastic container. From this load, six 3-kg samples were weighed and sealed in six small air tight containers for moisture treatment to determine moisture-density relationship for this litter. Moisture content of these samples was altered to achieve the target moisture contents (0%, 18%, 24%, 30%, 36% and 42% wet basis) by either drying or adding required amount of water. The moisture content and wet bulk density for each sample was measured, after samples were stored in sealed containers for 48 hour period to ensure uniform moisture absorption. Moisture content for the samples was determined using an OHAUS

Moisture Analyzer (MB45, OHAUS Corp., Pine Brook, NJ). Wet bulk Density of the samples was measured using an in-situ density measurement device.

Based on the mean moisture content and wet bulk density for each type of litter, different spreader and controller settings (treatments) were established to perform the testing. Table 3.1 provide the values of bulk density, gate height and target rate used for the rate controller settings. These values were entered in the Spreader Control Software setup menus prior to each test.

Table 3.1. Summary of broiler litter characteristics, density treatments, spreader gate height and the corresponding target application rate programmed into the Topcon X20 rate controller.

Type	Moisture Content (%)	Wet Bulk Density (kg/m^3)		Gate Height (cm)	Target Rate (kg/ha)
		Correct	Incorrect		
A	32	416.5	352.4	17.8	1743
					3486
				34.9	3424
					6848
B	28	480.6	416.5 544.6	17.8	1743
					3486
				34.9	3424
					6848

For each type of litter, different density treatments (values) were used in the X20 controller to measure the impact on discharge rate. For litter A, two density treatments (one correct density value: 416.5 kg/m^3; one incorrect density value: 352.4 kg/m^3) were used in the X20 rate controller whereas for litter B, three density treatments (one correct density value: 480 kg/m^3; two incorrect density values: 416.5 and 544.6 kg/m^3) were utilized (Table 3.1). The only difference between tests for each litter type was the inputting the density values (correct and incorrect) in X20 controller, not the actual density of the litter. Four application rates were calculated based on the gate height of 17.8 and 34.9 cm (two rates at each gate height) and set in the X20 controller as the target rates (Table 3.1). Treatments for bulk density and application rate were randomized within all the tests whereas gate height was blocked within each density treatment. Three replications were conducted for a total of 108 tests. All equipment was calibrated based on manufacturer's published literature (Chandler Equipment Company, Gainesville, Ga.) before conducting any tests. Litter A was used for calibrating the spreader and same calibration settings were used for litter A and B throughout the testing.

3.4.2 CONVEYANCE TESTS

Conveyance tests were conducted at the Biosystems Engineering facility at the E.V. Smith Research Center, Shorter, AL. For these tests, the rear divider was removed and a cardboard slide was used to allow litter to be easily conveyed into a collection container (227-kg capacity) for weighing (Figure 3.1). Prior to each test, the X20 controller settings were manually entered within the setup menus to match the appropriate treatment. Once the desired settings were typed into the X20, a test was run by turning on the controller master switch. Accumulated material collected in a collection container was weighed and documented along with the total conveyed mass read from the Spreader Control Software. The front roller speed (rpm) was measured with a standard tachometer. The distance travelled by the conveyor chain and total test time were also recorded.

Figure 3.1. Spreader setup used during conveyance testing illustrating fabricated chute for funneling litter into the plastic, collecting container.

3.4.3 Uniformity Tests

Field tests were performed according to ASABE Standard S341.4 (ASABE Standard, 2009). A single row of 19 pans, uniformly spaced at 0.9-m, with pans on either side of the center pan removed to allow the tractor and spreader to pass unobstructed, was used for calibration and during the pan tests (Figure 3.2). Experiments were conducted in a level field with tarps used to capture litter not collected by the pans. The spreader hopper was filled to at least 40% to 50% capacity (*ASABE Standard*, 2009) during all tests. Collection pan dimensions measured 50.8-cm long × 40.6-cm wide × 10.2-cm tall with a 5.1-cm tall, 10.2-cm grid used to prevent material loss (*ASABE Standard*, 2009). The spreader was calibrated at a target application rate of 4480 kg/ha at a gate height of 17.8 cm, a spinner speed of 650 rpm, a ground speed of 8 km/h, and 9.1-m swath width.

Figure 3.2. Tractor, litter spreader, and collection pan matrix used during pan testing.

An AB line was established for the RTK autoguidance system in order to maintain the tractor and spreader centered on the pans throughout testing. Prior to each test, the appropriate spreader settings were entered into the Spreader Control Software for each test. Conveyor and spinner-discs were turned on from the controller master switch before the spreader transversed the pans. After each test, material collected in each pan was placed in a container and weighed using an OHAUS digital scale (OHAUS Scale Corp., Union, NJ). All data was saved in a MS Excel file for data analysis.

3.4.4 Data Analysis

The conveyance test analysis consisted of taking the accumulated mass of litter collected in the container and converting it to a “discharge” rate (kg/rev) using the test time and conveyor speed (Equation 3.1). Mean actual discharge rate (kg/rev) and standard deviation (kg/rev) were calculated for the three replications at each setting used. Mean percent error (%) for each test setting was determined by comparing the mean actual discharge rate to the mean theoretical (target) discharge rate provided by the Spreader Control Software. Actual and theoretical discharge rates were compared and plotted to evaluate the impact of bulk density on conveyor discharge for both litter samples.

$$Discharge\ rate\ \left(\frac{kg}{rev}\right) = \frac{Weight\ of\ material\ (kg) \times test\ time\ (\text{min})}{conveyor\ speed\ (rpm)} \tag{3.1}$$

Field data analysis consisted of converting the amount of litter collected in each pan to an "actual" application rate (kg/ha) applied at that transverse location. Mean single-pass and simulated overlap (progressive method; *ASABE Standard*, 2009) distribution patterns were generated. For distribution patterns, the 0.0 m transverse position on the plots represented the spreader centerline while negative and positive transverse positions represented the left and right side, respectively from the centerline. The single-pass and overlap patterns were plotted to visualize any differences between treatments. From the overlap pattern data, the mean, actual application rate by treatment and coefficient of variation (CV) was calculated to evaluate spread accuracy and uniformity, respectively. Actual and theoretical application rates were compared and plotted to assess the impact of density on spreader performance.

A standardized distribution pattern at each density treatment was generated by dividing the application rate at each transverse location of the single-pass pattern by the calculated simulated, mean overlap rate. This standardization approach provides a method for unit-less representation of pattern data. The area under the standardized patterns (curves) is equal to one and therefore allows the direct comparison of distribution patterns at different transverse locations irrespective of the rate. An analysis of variance (ANOVA) was conducted on the standardized pattern data using SAS (Statistical Analysis Software, SAS Inst., NC) to determine possible statistical differences between patterns at the 352.4 and 416.5 kg/m^3 density treatments for litter A and, between patterns at 480.6 and 544.6 kg/m^3 density treatments for litter B. An

ANOVA analysis was also performed on the standardized data to check for statistical differences between the patterns for litter A and B.

3.5 Results and Discussion

The mean moisture content (MC) and wet bulk density (BD) for the two types of broiler litter is presented in Table 3.2. Statistical testing showed that the mean moisture contents and bulk densities for litter A and B were significantly different ($p<0.05$). Litter A had a higher MC than litter B but lower BD. This result indicated that the physical characteristics between these two sources of litter were different. Also, litter A had more characteristic variability than B as indicated by the standard deviation values for moisture and bulk density in Table 3.2. This variability was also an observable difference during testing.

Table 3.2. Mean moisture content and wet bulk density for the two types of litter used in testing.

	Moisture Content (%)		Wet Bulk Density (kg/m^3)	
Type	Mean	Std. Dev.	Mean	Std. Dev.
A	32.1	1.0	416.5	13.1
B	28.4	0.7	480.6	8.8

Figure 3.3 shows the moisture-density curve for litter A. A strong linear relationship between the moisture content and bulk density (w.b.) was observed with a R^2 value of 0.99. The bulk density increased with increase in the moisture content of the litter as reported in the past studies (Malone et al., 1992; Glancey and Hoffman, 1996; Thirion et al., 1998). The mean dry bulk density (i.e. 0% MC) for the litter was determined as 304.9 kg/m^3. This data showed that litter density was dependent on its moisture content and varied with litter moisture. It is believed that a similar linear curve between moisture and bulk density exists for all types of broiler litter obtained from different sources and can be generated. The moisture-density curve could be used

to provide rapid moisture and density information for real-time application control on a litter spreader.

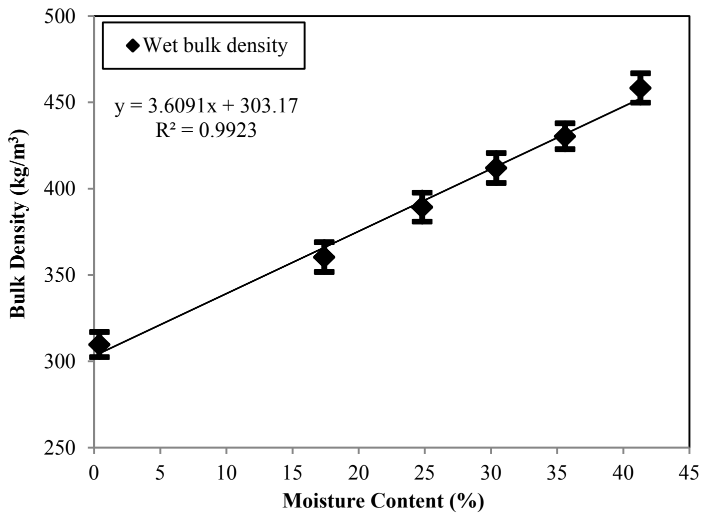


Figure 3.3. Plot illustrating moisture-density relationship for broiler litter A (vertical bars represent the standard deviation at each moisture content).

3.5.1 CONVEYOR DISCHARGE RATE ANALYSIS

Tables 3.3 and 3.4 summarize the conveyor discharge rate results. Actual discharge rates obtained using the actual density values were near the theoretical rates calculated by the X20 controller with rate errors less than ±5% (-4.8% − 1.8%). The virtual or incorrect density treatments produced higher rate errors (>±15%) which were expected. For litter A, using the incorrect density value of 352.4 kg/m^3 versus an actual litter density of 416.5 kg/m^3, resulted in higher actual discharge rates (>17.0%) than the theoretical target rates. For litter B, higher (>15.6%) and lower discharge rate errors (>-15.3%) were recorded for incorrect density values of 416.5 kg/m^3 and 544.6 kg/m^3, respectively compared to smaller errors (<±5%) for an actual density of 480.6 kg/m^3. It was noticed that using a lower incorrect density value (416.5 kg/m^3) than the actual density value (480.6 kg/m^3) generated higher or positive rate errors whereas using a higher incorrect density (544.6 kg/m^3) produced lower or negative errors. Higher standard deviation values occurred for the actual discharge rates for litter A which was contributed to the larger characteristic variation in litter A.

Table 3.3. Summary of conveyance tests for broiler litter A; actual density (w.b.) = 416.5 kg/m^3.

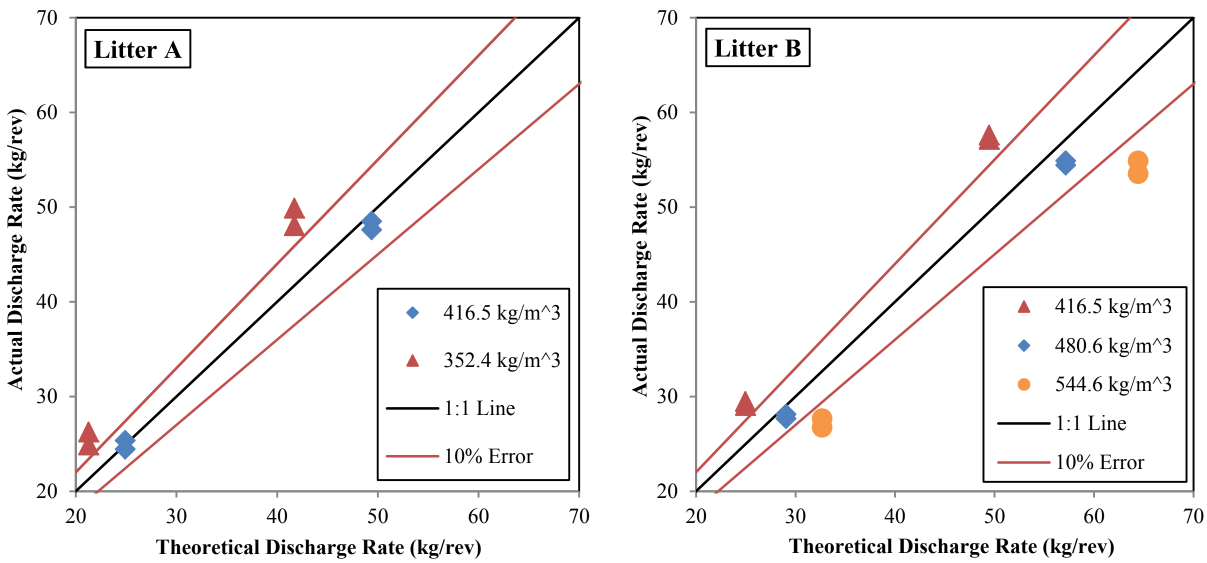
	Controller Settings						
Treatment ID	Bulk Density (kg/m^3)	Gate Height (cm)	Target Rate (kg/ha)	Mean Discharge Rate (kg/rev) Theoretical	Actual	Percentage Error (%)	Standard Deviation (kg/rev)
E	416.5	17.8	1743	24.9	25.4	1.8	1.6
F	416.5	17.8	3486	24.9	24.5	-1.8	3.1
G	416.5	34.9	3424	49.4	48.5	-1.8	4.4
H	416.5	34.9	6848	49.4	47.6	-3.6	2.8
E1	352.4	17.8	1743	21.3	26.3	23.4	4.5
F1	352.4	17.8	3486	21.3	24.9	17.0	1.2
G1	352.4	34.9	3424	41.7	49.9	19.6	4.6
H1	352.4	34.9	6848	41.7	48.1	15.2	1.4

Table 3.4. Summary of conveyance tests for broiler litter B; actual density (w.b.) = 480.6 kg/m^3.

	Controller Settings						
Treatment ID	Bulk Density (kg/m^3)	Gate Height (cm)	Target Rate (kg/ha)	Mean Discharge Rate (kg/rev) Theoretical	Actual	Percentage Error (%)	Standard Deviation (kg/rev)
P	480.6	17.8	1743	29.0	27.7	-4.7	0.7
Q	480.6	17.8	3486	29.0	28.1	-3.1	0.6
R	480.6	34.9	3424	57.2	54.4	-4.8	1.5
S	480.6	34.9	6848	57.2	54.9	-4.0	1.7
P1	416.5	17.8	1743	24.9	29.1	16.4	1.4
Q1	416.5	17.8	3486	24.9	29.5	18.2	1.0
R1	416.5	34.9	3424	49.4	57.6	16.5	2.0
S1	416.5	34.9	6848	49.4	57.2	15.6	2.5
P2	544.6	17.8	1743	32.7	27.7	-15.3	1.1
Q2	544.6	17.8	3486	32.7	26.8	-18.1	0.8
R2	544.6	34.9	3424	64.4	54.9	-14.8	2.6
S2	544.6	34.9	6848	64.4	53.5	-16.9	1.5

Figure 3.3 presents the comparison of actual versus theoretical discharge rates. The 10% error line represents an acceptable error margin. It was observed that using the correct density value produced discharge rates along the desired 1:1 or well less than 10% for both litter types.

However, the incorrect density treatments generated discharge rates outside the 10% range thereby indicating the importance of using the correct density value within a rate controller to maintain conveyance accuracy.



(a) **(b)**

Figure 3.3. Actual versus theoretical discharge rates during conveyance tests for broiler litter (a) A: actual density = 416.5 kg/m^3 and (b) B: actual density = 480.6 kg/m^3.

3.5.2 Field Application Rate Analysis

Tables 3.5 and 3.6 present the application rate summary data for the pan tests. Higher and lower application rates than the target rates occurred in the field using an incorrect density value for litter A and B, respectively. For both types of litter, using the correct density value within the Spreader Control Software yielded smaller application errors (<±10%) compared to large errors (-21.4% to 16.2%) for an incorrect density value. The computed CV's for both types of litter ranged from 23.4% to 30.3%, except for litter A, test D which resulted in a CV of 18.9%. Typically, one would expect lower CV's for a more uniform material (litter B) than for a less uniform (litter A).

Table 3.5. Summary of pan tests for broiler litter A; actual density (w.b.) = 416.5 kg/m^3.

	Controller Settings					
Treatment ID	Bulk Density (kg/m^3)	Gate Height (cm)	Target Rate (kg/ha)	Mean Application Rate (kg/ha)	Percentage Error (%)	CV[a] (%)
E	416.5	17.8	1743	1626	-6.7	28.9
F	416.5	17.8	3486	3172	-9.0	26.5
G	416.5	34.9	3424	3171	-7.4	24.8
H	416.5	34.9	6848	6319	-7.7	18.9
E1	352.4	17.8	1743	2031	16.5	28.9
F1	352.4	17.8	3486	4387	25.8	30.3
G1	352.4	34.9	3424	4097	19.6	23.4
H1	352.4	34.9	6848	7955	16.2	27.2

a) CV represents the Coefficient of Variation or uniformity of spread

Table 3.6. Summary of pan tests for broiler litter B; actual density (w.b.) = 480.6 kg/m^3.

	Controller Settings					
Treatment ID	Bulk Density (kg/m^3)	Gate Height (cm)	Target Rate (kg/ha)	Mean Application Rate (kg/ha)	Percentage Error (%)	CV[a] (%)
P	480.6	17.8	1743	1628	-6.6	27.0
Q	480.6	17.8	3486	3190	-8.5	26.8
R	480.6	34.9	3424	3171	-7.4	27.4
S	480.6	34.9	6848	6243	-8.8	30.3
P2	544.6	17.8	1743	1400	-19.7	26.3
Q2	544.6	17.8	3486	2838	-18.6	29.1
R2	544.6	34.9	3424	2693	-21.4	27.7
S2	544.6	34.9	6848	5637	-17.7	24.8

a) CV represents the Coefficient of Variation or uniformity of spread

Figure 3.4 provides a comparison of actual versus theoretical application rates for both litter A and B. These data illustrated that the actual application rates when using an incorrect density value tended to be higher and lower for litter A and B, respectively than the theoretical rates. Data points outside the 10% error range indicated operation beyond the allowable limit. These results were in agreement with the conveyance testing results highlighting the need to use the correct density value within a spreader rate controller to accurately meter litter.

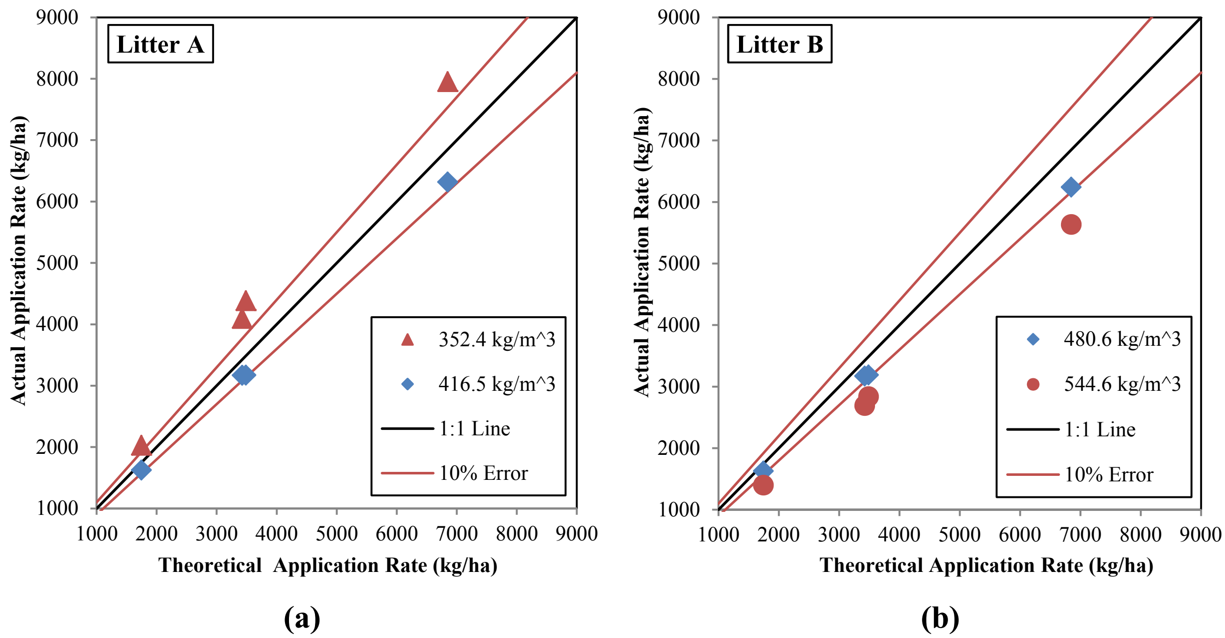


Figure 3.4. Actual versus theoretical application rates during pan tests for broiler litter A; actual density = 416.5 kg/m^3 (a) and litter B; actual density = 480.6 kg/m^3 (b).

3.5.3 Single-Pass Pattern Analyses

The overall mean, single-pass patterns at different density and rate treatments for both types of litter are illustrated in Figure 3.5. A "W" shape pattern existed for both types of litter but was the best achievable pattern for this spreader and litter combination. This "W" pattern was consistent at all density and application rate treatments. In comparison between the patterns at different rate treatments, it was observed that the pattern peak varied with application rate. The general trend was that the central peak increased as the rate increased. For example, the patterns at the 6848 kg/ha treatment had higher peaks than the patterns at the 1743 kg/ha.

Similar trends were observed for comparison between the patterns at the different density treatments for both litter types. The intensity of the "W" shape, especially at the center, varied between the density treatments due to different actual application rates or mass flow associated with these treatments. Within each litter type, the pattern central peak was higher at the lower density treatment than the peak at the higher density treatment for each rate treatment. For example, the pattern at the 352.4 kg/m^3 density treatment for litter A had a higher peak at the center than the pattern at the 416.5 kg/m^3 density treatment for 1743 kg/ha (Figure 5a). This change in magnitude occurred due to higher actual application rate or mass flow at the lower density treatment than mass flow at the high density treatment.

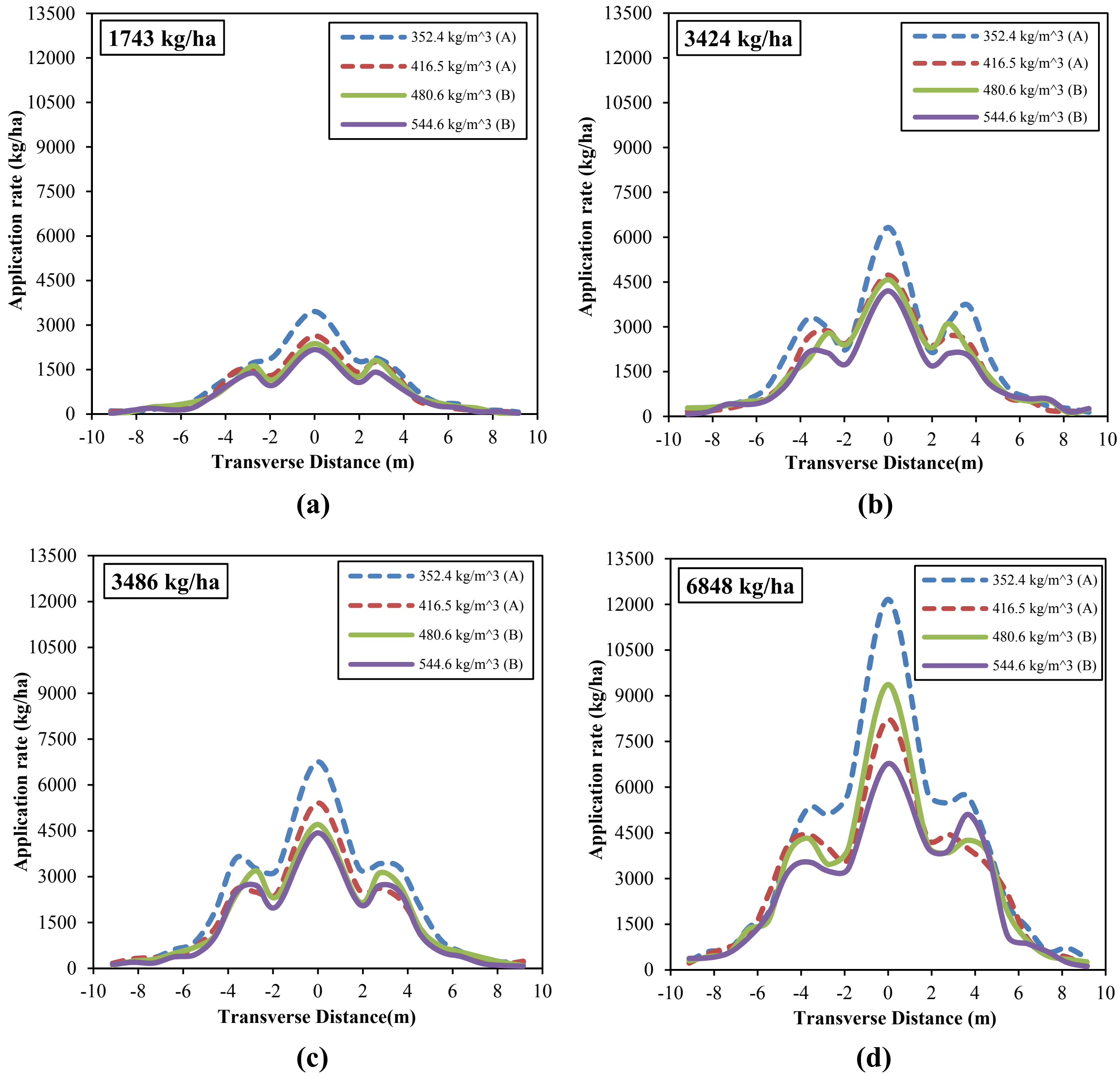
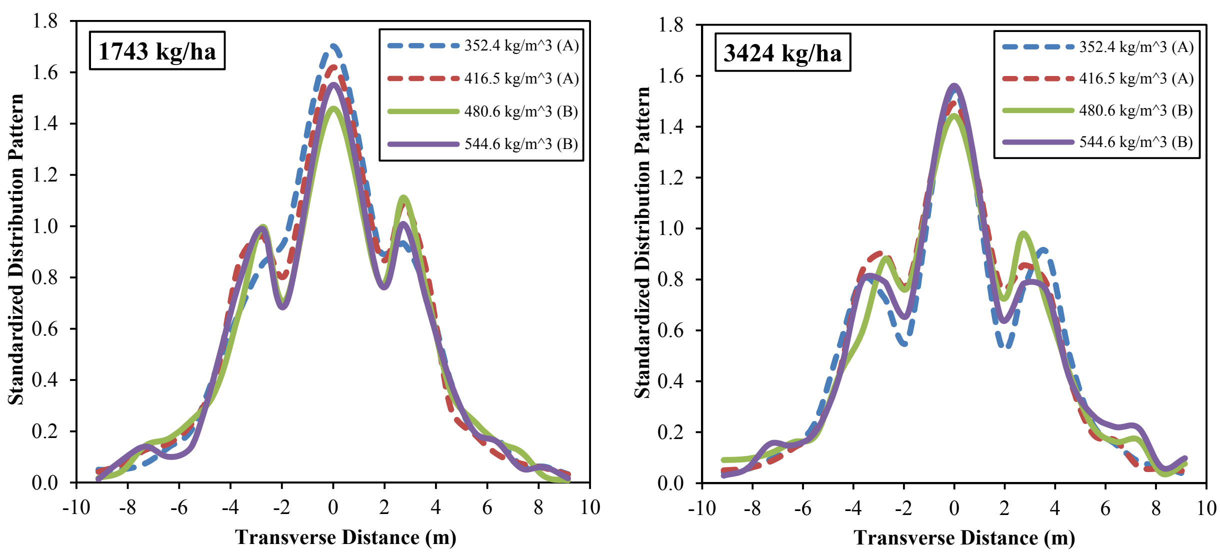


Figure 3.5. Comparison of overall mean single-pass distribution patterns at different density treatments by application rate and litter type.

3.5.4 STANDARDIZED PATTERN ANALYSIS

Figure 3.6 illustrates the standardized distribution patterns at different density treatments for litter A and B. Within both litter types, differences between the patterns were mainly observed between the -3.7 and 3.7 m transverse locations, on either side of the spreader centerline. For example, the patterns at the 352.4 and 416.5 kg/m^3 density treatments for litter A were different at 0, 1.8 and 2.7 m locations on either side of the centerline for 3424 kg/ha. The ANOVA results for these patterns also showed significant differences at -1.8 m (p=0.0023) and 1.8 m (p=0.0159) locations at same rate treatment. Similarly, for litter B at 3424 kg/ha, the patterns at the 480.6 and 544.6 kg/m^3 density treatments differed at the 1.8 and 2.7 m transverse locations on either side of centerline. The ANOVA results also indicated statistical differences between these patterns at -3.7 m (p=0.0029) and -1.8 m (0.0480) locations. Similar trends were observed in other rate treatments as well, for both litter types.



(a) (b)

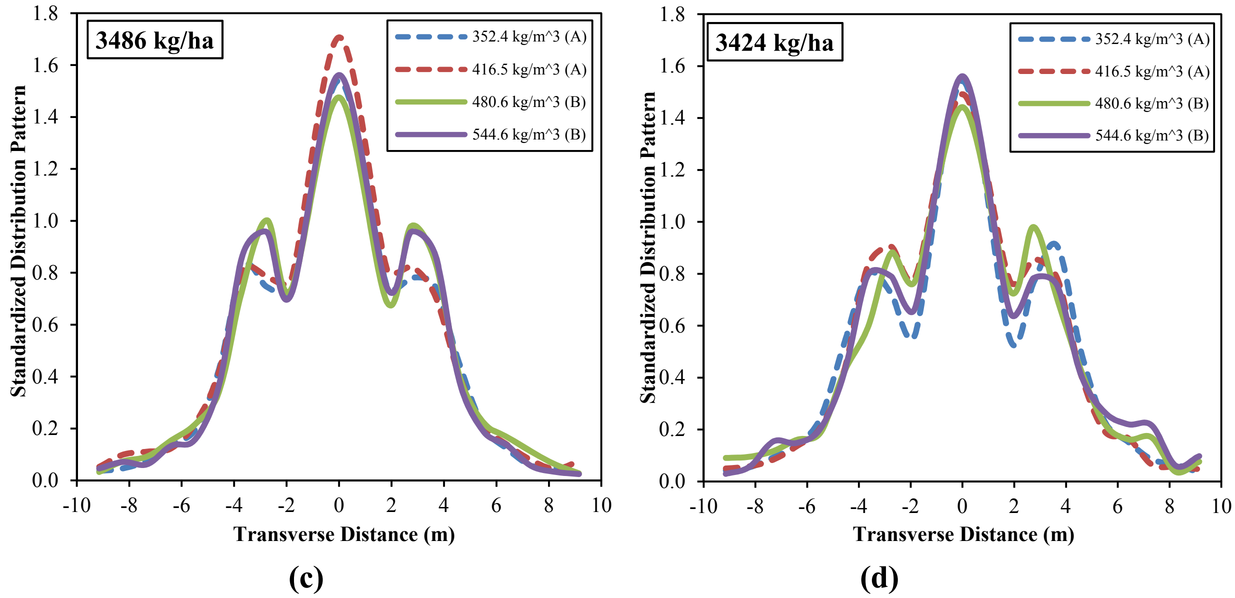


Figure 3.6. Comparison of standardized, mean single-pass distribution patterns at different density treatments by application rate and litter type.

Comparison based on litter type also indicated a few differences between litter A and B patterns at the 1.8 and 3.7 m locations on either side of the centerline for all rate treatments. The ANOVA analysis on standardized data for comparison between litter A and B patterns indicated significant differences at a few transverse locations such as -3.7 m ($p=0.0085$) and -1.8 m ($p=0.0008$) for 3424 kg/ha, and -3.7 m ($p=0.0055$) and -4.6 m ($p=0.0063$) for 6848 kg/ha treatment. Though the ANOVA results on the pattern data did not indicate significant differences at all the observed locations ($p>0.05$) in Figure 3.6 but practical differences existed between patterns. Theoretically, correct density values within the rate controller for individual rate treatments should generate the same single-pass and standardized patterns. The observed differences in the patterns within each rate treatment showed the influence of density treatments, used in the Spreader Control Software, on the distribution patterns. These differences can be attributed to differences in mass flow. As mass flow increases, so does the magnitude of the resulting pattern.

Results for this study indicated that wet bulk density was linearly related to its moisture content for litter A and could be used to determine density from litter moisture information with proper moisture-density curve. The incorrect density value applied in the Spreader Control Software affected the resulting litter application rate and distribution pattern by varying the actual conveyor discharge (mass flow). These findings supported the idea of using a correct density value within a spreader rate controller. However, the moisture variability found in litter tends to produce density variation within a load, making it difficult to use one accurate density value in the rate controller for litter application. Hence, the traditional approach of using a constant density value within a rate controller can produce high application errors (>±10%) if density variation exists within the litter. The proposed solution would be inclusion of real-time moisture content or density data as a secondary feedback to a spreader rate controller during litter application. This feedback data can be used to update real-time density values, with the help of a proper moisture-density calibration curve uploaded in the Spreader Control Software. The secondary feedback approach would help better control and manage the desired target application rates while keeping off-rate errors to less than 10%. In the future, real-time density updates within a spreader rate controller could conceivably be used for making on-the-go spreader hardware adjustments (e.g. spinner speed) in order to maintain acceptable uniformity of spread of litter.

3.6 SUMMARY

The conveyor discharge rates and distribution patterns for a typical spinner-disc spreader were characterized to determine bulk density effect on field application of broiler litter. Initial results concluded that wet bulk density of litter A was dependent on its moisture content and increased with an increase in moisture content. Rate analysis results showed that litter density affected conveyor discharge rates based on both conveyance and pan tests. Higher rate errors (>±15%) were generated during both tests when incorrect density values were applied in the Spreader Control Software compared to low errors (<±10%) when using the correct litter density value.

Distribution pattern analysis indicated that the peak of the “W” shaped single-pass patterns at different density treatments increased with increase in the actual application rate or conveyor mass flow. Comparison among standardized patterns reflected differences in the patterns at correct and incorrect density treatments between the -3.7 and 3.7 m transverse locations for both litter types (A and B). Differences between the patterns were attributed to change in the conveyor mass flow which was caused by the incorrect density treatments used within the rate controller.

Overall, high rate errors and differences in distribution patterns highlighted the importance of using correct density values within a spreader rate controller for accurate litter metering and distribution. Inclusion of an appropriate inline moisture or/and density sensing technology for accurate determination and incorporation of real-time density values within a rate controller can help in maintaining an acceptable application accuracy (within 10%) when applying litter with a spinner-disc spreader.

CHAPTER FOUR

EVALUATION OF CAPACITANCE TYPE MOISTURE SENSOR FOR MEASURING BROILER LITTER MOISTURE CONTENT

4.1 ABSTRACT

A simple, low cost capacitance type grain moisture sensor was tested for measuring broiler litter moisture content. The sensor response (based on differential voltage) was recorded over a range of 16%-43% moisture content (w.b.) (10 samples at 3% interval) for broiler litter. Three different densities (A: loose bulk, B: medium and C: highly dense) were used as treatments at each moisture level. Initial data analysis indicated that litter density affected the sensor output voltage. The sensor generated a linear output within the 16%-31%, 16%-28% and 16%-21% moisture range at density treatments A, B and C, respectively. Linear regression models (Model 1, 2 and 3 at density treatment A, B and C, respectively) relating sensor output voltage to moisture content generated high R^2 values within 0.96-0.99 at each density treatment. The calibration errors (SEC and RMSEC) for all the models were less than 1%. Validation results also provided high linear relationship (R^2 = 0.90-0.94) between predicted and actual moisture values. Both model 1 and 2 generated low prediction errors (<1.2%) whereas model 3 produced high prediction errors (>1.8%). Model 2 produced the best results by predicting moisture values with a good R^2 value of 0.92 and low SEP and RMSEP values of 1.0483% and 1.0128%, respectively. The overall results suggested that besides few limitations, properly calibrated sensor has a good potential for real-time moisture measurements of broiler litter.

4.2 INTRODUCTION

Due to environmental regulations, there is an increasing need for rapid methods of analyzing physical and chemical properties of animal manures to more efficiently utilize them as fertilizer and avoid unnecessary environmental contamination. Presently, analyses of poultry manures requires the use of several methods for determining the constituents of interest i.e. nutrient content, moisture content, minerals etc. Moisture content is important because it affects other litter properties such as bulk density and compressibility. Litter physical properties, especially moisture content and density, are important parameters for accurate and uniform land application of the litter. Wide moisture range (15% - 40%) found in poultry litter due to different feeding and management systems (Lague et al., 2005) is believed to contribute towards inacceptable distribution obtained with spinner-disc spreaders. Accurate moisture determination of poultry litter is thereby crucial for improving application. This will require real-time moisture analysis of the litter before or during application.

Currently, moisture content in biomaterials such as poultry litter is determined through standard oven methods that involve tedious laboratory procedures and long oven-drying periods (24-72 hours). In contrast, rapid methods of moisture measurement offer the possibility of quick analysis of samples with little or no sample preparation while simultaneously determining other material properties. Rapid methods are more suitable for real-time moisture analysis since the ultimate target would be inline moisture measurement of poultry litter on spinner spreaders during application.

Moisture measurement methods are usually classified as contact or non-contact based on material contact with the sensing device. Capacitance and resistance type moisture meters are common contact type moisture measurement devices for biomaterials. These low cost and easy-to-use sensors can provide moisture information in agricultural materials with reasonable amount of accuracy (within 0.5%-1%). These sensors have been used by researchers for moisture measurement in forage, cotton etc. and have not been investigated for moisture measurement in poultry litter. Marcotte et al. (1999) reviewed various moisture measurement sensors during forage and hay harvest and suggested that capacitive sensors would be most suitable to estimate moisture during conveying. Osman et al. (2001 and 2003) developed a parallel-plate capacitor sensor for measuring moisture in hay and reported good correlation between the sensor's output and hay moisture. Results from a study by Savoie et al. (2011) indicated that dynamic and continuous measurement of moisture during forage drying was feasible with a relatively low-cost resistive type sensor but further validation was needed. The only study on the potential of a capacitance sensor for measuring moisture content in poultry litter was carried out by Mendes et al. (2008). They used four EC-5 capacitance-type sensors for measuring moisture content in meat-bird (broiler and turkey) litters and laying-hen manure. Moisture content for the broiler, turkey litter and layer manure varied from 27.1% to 55%, 22.8% to 56.1% and 11.0% to 75.0%, respectively. The authors found that the soil moisture measurement sensor can be effectively used to measure poultry litter moisture content on a real-time basis with proper calibration. No other studies have reported the use of capacitance sensors for moisture measurement in poultry litter. The satisfactory performance of these sensors with biomaterials along with their relatively low cost makes capacitance sensors a promising option for poultry litter. However, further evaluation still needs to be conducted for their use in poultry litter moisture measurement and the feasibility of using these sensors to control the application of litter.

The idea behind this study was that a capacitance sensor could be applied to a litter spreader for inline and real-time moisture determination. This feature could be used to provide litter moisture information as feedback to a rate controller. For litter application, a rate controller requires litter density as an important setup parameter to manage the conveyor mass flow based on the density value. Litter density can be determined from moisture information if a relationship between moisture content and litter density can be established. Past research showed that density variation can exist within litter due to moisture variability and can affect spreader performance by producing high rate errors. Therefore, the assumption for this study was that real-time moisture information from a capacitance sensor could be used for updating density values within the rate controller for accurate litter conveyance. The moisture/density secondary feedback would help in improving litter application by accounting for any density variations.

4.3 Sub-Objectives

The objectives of this study were to: (1) evaluate the suitability of a capacitance type moisture sensor for real-time moisture measurement of broiler litter and, (2) development of a calibration model for predicting moisture content in broiler litter using a capacitance based sensor.

4.4 Methodology

4.4.1 Sample Preparation

A small load of litter was acquired in a plastic container (50 kg) from bulk litter. Ten samples were randomly collected from the container and placed in sealed bags to determine the mean moisture content and bulk density for this litter. Further, 3-kg samples were weighed out of this litter and sealed in ten small air tight containers. The initial moisture content of these samples was altered to achieve the required moisture contents by either drying or adding required amount of water. The target moisture content for the ten samples were 16%, 19%, 22%, 25%, 28%, 31%, 34%, 37%, 40% and 43% (w.b.). Samples were thoroughly mixed and set for 48 hours to ensure uniform moisture absorption within each sample. The mean moisture content and bulk density for each sample was then measured after this 48 hour period.

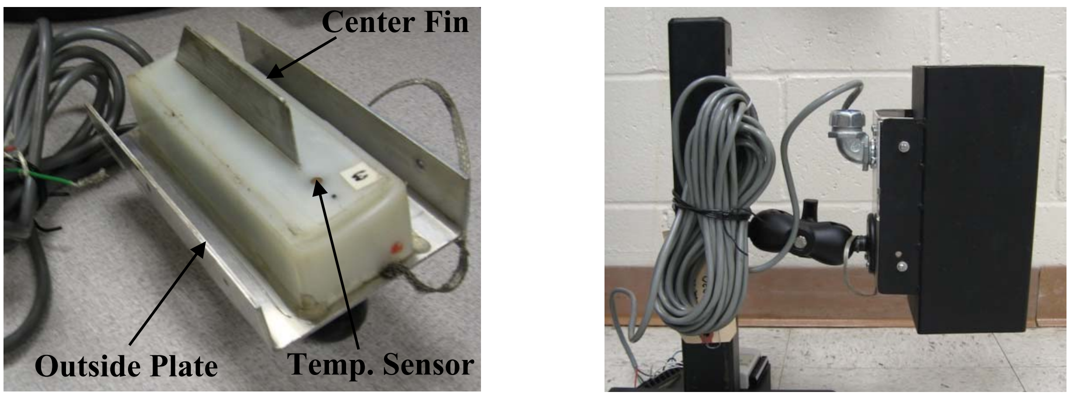
Moisture content of the samples was measured by using standard oven method (*ASAE Standards*, 2003). Five 5-g samples from each litter sample were placed in the oven (at 105^{o}C). The dry mass of the samples was measured after 48 hours. Moisture content of each sample was determined from dry mass using Equation 4.1. The mean moisture content for each sample was computed from the replication data and used as the actual moisture content.

$$Moisture\ Content\ (\%) = \frac{Initial\ mass\ of\ sample\ before\ drying - mass\ of\ sample\ after\ drying}{Initial\ mass\ of\ sample\ before\ drying} \times 100 \qquad \text{Eqn.}\,(4.1)$$

The validation data set consisted of 15 litter samples acquired from different production houses in North Alabama. These samples contained different levels of moisture content as well as physical variability. The mean moisture content for each sample was determined by the standard oven method (*ASAE Standards*, 2003) and used as the reference moisture content during validation.

4.4.2 Test Setup and Data Collection

A stainless steel capacitance sensor (David Manufacturing Corporation, DMC Assumption, IL), shown in Figure 4.1(a), typically used for measuring grain moisture was used in this study. The sensor consisted of a center fin with an outside U-shape plate, both acting as electrodes, and measured the change in dielectric properties of air plus sample placed between these two electrodes. A differential voltage signal, corresponding to the change in dielectric properties between the plates, was measured as the sensor output. An AD592 temperature transducer installed within the sensor provided a temperature signal and was used to determine the sample temperature during testing. This sensor was mounted in a rectangular iron housing, which measured 25.4-cm × 9.5-cm × 9.5-cm in dimensions (Figure 4.1b). The housing was used so that a known sample volume can be placed in it for each test and that litter remained in complete contact with the center fin of sensor. Two hard styrofoam caps were used to close both ends of the rectangular housing during testing. Each cap was marked with 2 solid lines spaced at 1.5 cm from one end for establishing density treatments during a test by moving the cap inside the housing a known distance and thereby knowing the exact volume.



(a) **(b)**

Figure 4.1. (a) DMC capacitance sensor and (b) housing with installed sensor used for data collection.

A LabView program (Version 10.0.1, 2010) was developed and used with a USB-6009 controller (National Instruments, Austin, TX) to acquire and log voltage signals (moisture and temperature voltage) generated by the DMC capacitance sensor. Temperature (˚F) for each sample was calculated within LabView using the temperature signal and was displayed along with differential voltage output. A 0-20 V, 0.5 A output DC power supply (Model E3630A, Agilent Technologies, Santa Clara, CA) was used to provide the required operating voltage (12-20 V) to the sensor. The test setup with various components is presented in Figure 4.2.

Data collection consisted of filling the housing with a litter sample in loose bulk form to a known volume (22.2-cm × 9.5-cm × 9.5-cm) with the end caps placed on either end of the housing. The mass of litter that filled the known volume was measured and used to calculate the loose bulk density for each sample (termed Density Treatment A). Once started, the LabView program logged the sensor output for 1 minute duration at a frequency of 1 voltage point per second and displayed the mean values for differential voltage and temperature at the end of each test. After the first measurement, the end caps were moved up to the first marked line, 1.5-cm into the housing from both sides, to attain a different dense litter density (termed Density Treatment B) by decreasing the holding volume (19.2-cm × 9.5-cm × 9.5-cm). The sensor output at this new density treatment was recorded again for 1 minute duration. The third and final measurement consisted of moving the end caps further into the housing up to second mark (1.5 cm from previous line, total 3 cm inside the housing) to reduce the holding volume to 16.2-cm × 9.5-cm × 9.5-cm for obtaining highly dense density value (termed Density Treatment C). The differential voltage along with temperature output was recorded at this litter density for each sample and saved for data analysis. A total of 30 tests were performed with 3 replications for each test.

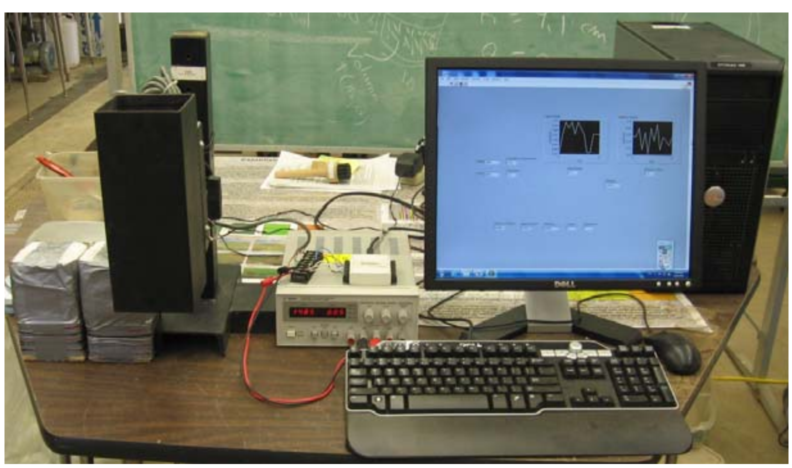


Figure 4.2. Test setup used for capacitance data collection for the broiler litter.

4.4.3 Data Analysis

Data analysis consisted of developing simple linear regression models for estimating moisture content in litter. Data was analyzed using Microsoft Excel (Microsoft Corporation, Redmond, WA) and SAS (Statistical Analysis Software Institute Inc., NC). Simple linear regression models were developed at each litter density treatment (Density A, B and C) using the measured differential voltage as a predictive variable and moisture content as the response variable. Statistical measures such as standard error of calibration (SEC) (Eqn. 4.2), root mean square error of calibration (RMSEC), and coefficient of determination (R^2) were calculated to evaluate these models.

$$SEC = \left(\frac{1}{n-p-1}\sum_{i=1}^{n} e_i^2\right)^{\frac{1}{2}} \tag{4.2}$$

where n is the number of observations, p is the number of variables in the regression equation with which the calibration is performed and e_i represents the difference between the observed and reference values for the ith observation.

The performance of calibration models was evaluated by fitting to validation data set for predicting the moisture content in litter samples, and calculating the standard error of prediction (SEP) obtained by comparing the reference values determined by the standard oven method with those predicted by the models (Eqn. 4.3), root mean square error of prediction (RMSEP) and coefficient of determination (R^2) values:

$$SEP = \left(\frac{1}{n-1}\sum_{i=1}^{n} (e_i - \bar{e})^2\right)^{\frac{1}{2}} \tag{4.3}$$

where n is the number of observations, e_i represents the difference between the predicted moisture content and that determined by the reference method for the ith observation, and $\bar{e}$ is the mean of e_i for all samples.

4.5 RESULTS AND DISCUSSION

Table 4.1 presents the summary statistics for the litter samples representing the calibration group. The determined mean moisture content for the samples was within ±0.4% difference from the nominal target moisture contents. The mean moisture contents were statistically different from each other (p<0.0001). The standard deviation values were between 0.1% and 0.3% indicating low moisture variation within reps.

Table 4.1. Mean moisture content and standard deviation (Std. Dev.) for the calibration litter samples.

Sample No.	Target Moisture Content (%)	Actual Moisture Content (%)		Diff. from Target (% MC)
		Mean	Std. Dev.	
1	16.0	16.2	0.3	0.2
2	19.0	19.3	0.2	0.3
3	22.0	22.1	0.2	0.1
4	25.0	25.2	0.2	0.2
5	28.0	28.3	0.2	0.3
6	31.0	31.4	0.1	0.4
7	34.0	34.3	0.3	0.3
8	37.0	37.0	0.2	0.0
9	40.0	40.4	0.2	0.4
10	43.0	42.9	0.1	-0.1

Figure 4.3 illustrates the voltage response curves at different density treatments for the capacitance sensor. The sensor generated output voltages ranging from 2 to 8.35 V corresponding to a moisture content range of 16% to 43% for the litter samples. The observed trend was that the sensor output voltage increased with increase in litter moisture content and bulk density. It was also observed that the sensor response was close to linear at all three density

treatments before a specified voltage was reached (termed as cut-off voltage). In this case, a cut-off voltage of 7.35V was determined. The reason behind establishing a 7.35 V as the cut-off value was that the response of sensor, beyond this cut-off voltage, was non-linear with no significant distinction between the output voltage values at different moisture levels. This value was also selected based on recommendation from the sensor manufacturer (DMC). The output voltage tended to reach a saturation zone (8.00 – 8.35V) after the cut-off point. This voltage range (8.00 – 8.35V) was also an operating reference voltage for the sensor and therefore limited the operability of this sensor beyond this point.

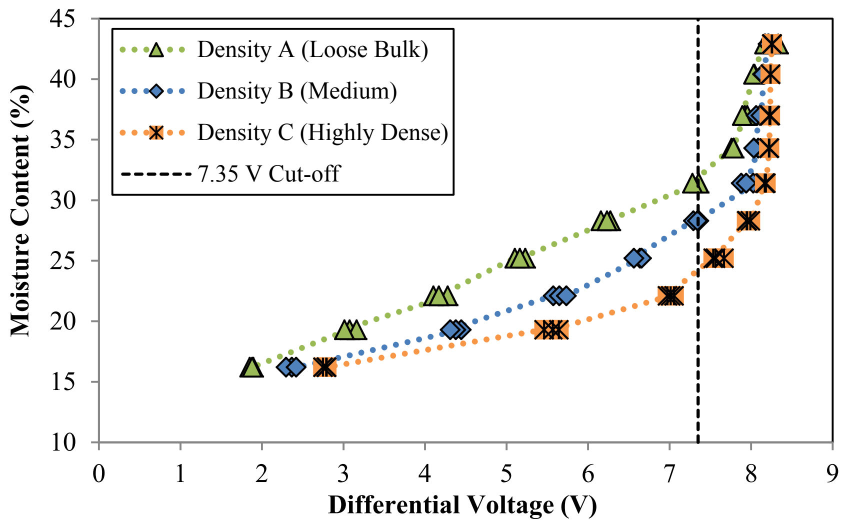


Figure 4.3. Voltage response curves for the capacitor sensor at different density treatments (cut-off represents voltage value beyond which the sensor response was non-linear).

In comparison among density treatments, the sensor output voltage was different at the same moisture levels for all three density treatments. Density treatment A produced a near linear response with data points distributed uniformly across the response line. Density treatments B and C did not generate as near a linear response. For density treatment A, the sensor generated linear response within the moisture range of 16% to 31% before the cut-off voltage was reached. The sensor did not respond well in the 34%-43% range while generating a non-linear output with little distinction between the output voltages within this moisture range. The sensor output for density treatment B was linear within the 16% to 28% moisture range and afterwards became non-linear for remaining moisture range. For density treatment C, the sensor produced a linear response only between 16% and 21% before reaching the cut-off voltage. The increase in litter density (density C) generated higher output voltages at the same moisture levels compared to density treatment A, the loose bulk density of litter. The sensor attained a cut-off voltage sooner due to the high output voltages and therefore worked only within the lower moisture range compared to the wider moisture range for density treatment A. Results indicated that litter density affected the sensor output and limited the operating moisture range for the sensor. These results suggest that the sensor can be effective within a certain moisture range (between 61% and 31% MC) depending on litter density.

4.5.1 CALIBRATION MODELS

The sensor output voltages, before the cut-off point, were plotted against the corresponding moisture contents for each density treatment (Figure 4.4). The calibration model for each density was developed by fitting a regression line to the calibration voltage data. For each model, voltage values before the cut-off voltage (7.35 V), was used for developing the model. Table 4.2 provides the results for the regression parameters and fitness measures. For density treatment A, a total of 18 voltage observations for 16%-31% moisture levels were used in the regression model, whereas for density treatments B and C, only 15 voltage observations between 16%-28% and 9 observations between 16%-22%, respectively were used in the regression model.

The linear regression for Model 1 and 2 followed similar trends (Figure 4.4) with comparable slopes and y-intercepts, whereas the regression for Model 3 followed a totally different trend with a high y-intercept (12.27) and small slope (1.35) compared to other two models. This result can be attributed to the varying voltage response of the sensor due to high density (density C) involved in this treatment compared to the sensor response at the other two density treatments (A and B).

Model 1 had the highest coefficient of determination (R^2) value of 0.99 showing a strong relationship between the sensor output and moisture content. Models 2 and 3 also showed comparable R^2 values of 0.96 and 0.98, respectively. The SEC and RMSEC values for all three models were less than 1% indicating low calibration errors. Model 1 had the lowest SEC and RMSEC values. Since all three models generated good linear trends, and low SEC and RMSEC values, they were all used for moisture content predictions for the validation group of data.

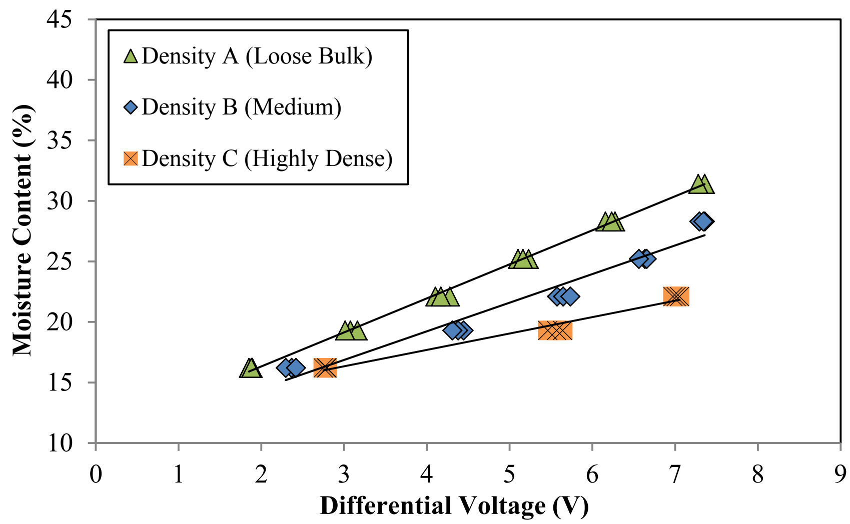


Figure 4.4. Regression lines for the capacitor sensor output at different density treatments.

Table 4.2. Regression parameters and fitness measures for the models developed for the calibration group.

Model	Density Treatment	No. of observations	Regression Parameters Intercept (β0)	Regression Parameters Slope (β1)	R^2	SEC (% MC)	RMSEC (% MC)
1	A	18	10.75	2.79	0.99	0.2417	0.2349
2	B	15	9.81	2.35	0.96	0.9001	0.8695
3	C	9	12.27	1.35	0.98	0.3853	0.3632

4.5.2 Validation

Table 4.3 presents the mean moisture content and standard deviation values for the litter samples of the validation group. The mean moisture content ranged from 17.4% to 28.8%. Standard deviation (SD) values were higher in a few of the validation samples (>0.5%) compared to low SD values (≤0.3%) observed in the calibration samples (Table 4.1), indicating more moisture variability within the samples.

Table 4.3. Mean moisture content and standard deviation for validation group litter samples.

Sample No.	Moisture Content (%) Mean	Moisture Content (%) Std. Dev.
1	17.4	0.3
2	19.1	0.6
3	20.0	0.3
4	21.0	0.6
5	21.1	0.3
6	22.8	0.5
7	23.4	0.4
8	24.1	0.4
9	24.5	0.9
10	24.8	0.7
11	27.2	0.8
12	27.3	0.7
13	27.4	0.6
14	28.6	0.5
15	28.8	0.5

Table 4.4 shows the fitness measures for the validation litter samples. The validation set also provided good R^2 values (0.90-0.94) for all three models indicating good relationship between the predicted and actual moisture contents of the litter samples. Model 1 (density treatment A) produced the highest R^2 value of 0.94 with SEP and RMSEC values of 1.1936% and 1.1531%, respectively. Model 2 and 3 also generated comparable R^2 values of 0.92 and 0.90, respectively. The SEP and RMSEP values for model 2 (1.0483% and 1.0128%, respectively)

were slightly lower than the values for model 1. This can be attributed to the difference between the density treatments used during data collection for Model 1 and 2. The voltage output of the sensor is directly related to change in dielectric constant of sample plus air between the electrodes. Generally, it is very hard to control the measurement space (material plus voids) between the electrodes. Theoretically, there should be no air spaces or voids along with the material between the electrodes for accurate measurement but during practical applications, it is very difficult to achieve the voids free (material only) measurement space. Higher number of air spaces or voids with the sample during measurement will result in high errors in the sensor output and thereby less accurate readings. Hence, the air spaces or voids inside the housing due to loose bulk litter (density treatment A) influenced the voltage output and produced higher error during prediction. Increasing the density (density treatment B) by compacting litter eliminated some of these spaces and produced slightly more accurate voltage readings. Model 3 generated the highest errors with SEP and RMSEP values of 1.7858% and 3.1605%, respectively. This model was calibrated within 16%-21% MC range and was good for predicting moisture content within this range only. Moisture prediction outside the range resulted in high errors in the moisture readings.

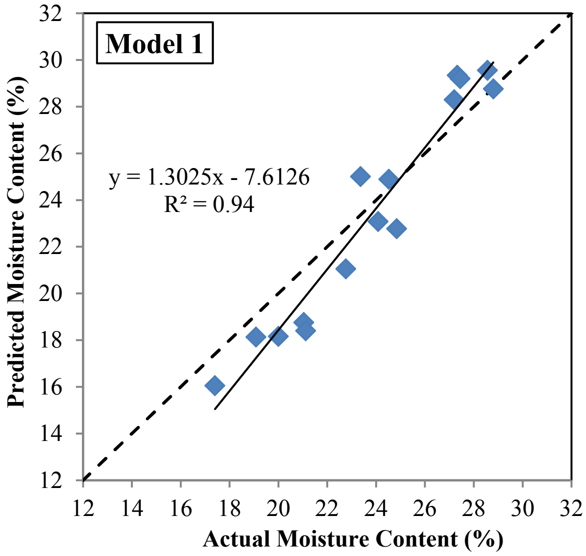
Table 4.4. Fitness measures of the validation group obtained from the models.

Model	Density Treatment	No. of observations predicted	R^2	SEP (% MC)	RMSEP (% MC)
1	A	15	0.94	1.1936	1.1531
2	B	15	0.92	1.0483	1.0128
3	C	15	0.90	1.7858	3.1605

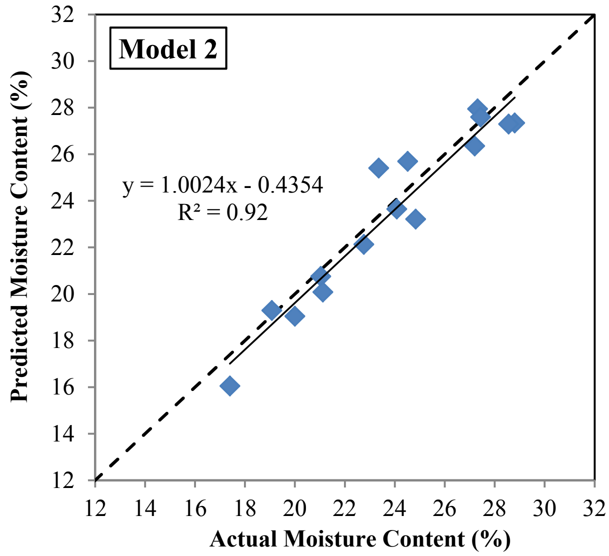
Figure 4.5 presents the comparison of the predicted and actual (reference) moisture values of the litter samples. The predicted moisture content values correlated well with their corresponding actual values with R^2 greater than 0.90 for all the equations. Linear regression

lines between the predicted and actual moisture content values along with the 1:1 (45^o) fit line are also presented in Figure 4.5. Theoretically, the slope and intercept of a regression line between predicted and actual values should be equal to 1 and 0, respectively for an ideal fit. The regression lines for Model 1 (Figure 4.5a) and Model 3 (Figure 4.5c) lacked accuracy. The lines were distinct from the expected 45^o angle with slope and intercept significantly ($p<0.0001$) different from one and zero. For Model 1, the predicted moisture values were both positively and negatively skewed over the full moisture range, while the predicted values for Model 3 were all negatively skewed. The regression line for Model 2 resulted in a close fit to the 45^o line, with slope and intercept not statistically different from one (p-value=0.2436) and zero (p-value=0.8146), respectively (Figure 4.5b). The line aligned quite well with the 1:1 line with slope and intercept values of 1.0024 and -0.4354, respectively. In comparison, Model 2 provided the best prediction results with high R^2, low SEP and RMSEP values indicating strong correlation between the predicted and actual moisture contents.

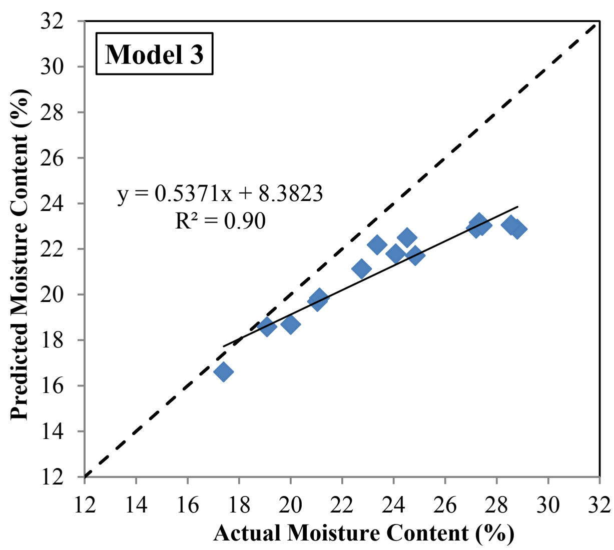
Results for this study indicated that this capacitance sensor in conjunction with a proper calibration equation can be used for real-time moisture measurement of broiler litter with certain limitations. Litter density impacted the working of the sensor and reduced the operating moisture range (16%-31%) within which the sensor operated satisfactorily. Also, the presence of air spaces along with litter between the sensor electrodes affected the sensor output and resulted in errors during moisture predictions. The idea of using this capacitance sensor on a litter spreader is feasible, but requires more research with improved sensor housing or installation equipment design to ensure full contact with litter and to account for the operational errors due to spreader vibrations during application. Also, proper sensor calibration along with accounting for litter density would be required to obtain acceptable moisture readings (within ±2%).



(a)



(b)



(c)

Figure 4.5. Comparison of predicted and reference moisture content values for the validation group litter samples.

4.6 SUMMARY

A capacitance sensor, typically used for measuring grain moisture, was evaluated for estimating real-time moisture content of broiler litter. The voltage response of the sensor was affected by litter density and increased with increase in density at the same moisture contents.

Also, an increase in litter density decreased the operating moisture range of the sensor. Calibration models (Model 1, 2 and 3) were developed at three different density treatments (A, B and C) using sensor output voltage to predict moisture content in the validation samples. All three models produced high R^2 values of 0.99, 0.96 and 0.98 during calibration. The SEC and RMSEC values were all three models were less than 1% indicating low calibration errors associated with these models.

Validation results also produced equally good R^2 values of 0.94, 0.92 and 0.90 for Model 1, 2 and 3, respectively. Model 2 generated the lowest SEP and RMSEP values of 1.0483 and 1.0128% with predicted moisture values strongly related to the actual values. Model 1 also produced low SEP (1.1936%) and RMSEP (1.1531%) values comparable to model 2, whereas model 3 generated the high SEP (1.7858%) and RMSEP (3.1605%) values. Model 2 provided the best results by predicting moisture values close to the actual moisture contents and producing a high R^2 (0.94) and low error values.

The capacitance sensor worked quite well for predicting litter moisture within each density treatment. With certain limitations, the sensor has a potential for real-time moisture measurement of broiler litter on a litter spreader. Proper sensor calibration along with improved housing design would be required for reliable sensor output during application. Also, density effect on sensor output needs to be considered and accounted for to generate accurate moisture estimates.

CHAPTER FIVE

NEAR-INFRARED SPECTROSCOPY FOR REAL-TIME MOISTURE CONTENT MEASUREMENT IN BROILER LITTER

5.1 ABSTRACT

Accurate and continuous measurement of moisture content would represent a significant improvement in broiler litter application using spinner-disc spreaders. A study was conducted to evaluate various near-infrared (NIR) wavelengths for predicting moisture content in broiler litter. Spectral absorption data between 1200-2200 nm was collected for 10 broiler litter samples with moisture content ranging between 16%-43%. Initial partial least squares analysis on spectral data indicated that strong absorption bands highly correlated to litter moisture occurred within 1400-1440 nm and 1900-1950 nm. Prediction models developed using absorbance values at 11 selected wavelengths between these bands (10 nm interval) for estimating litter moisture content showed high correlation (R^2 = 0.97-0.99) during calibration. Validation results provided high correlation as well (R^2 = 0.87-0.95) with standard error of performance (SEP) ranging between 0.8166% and 1.3609%. The regression models with absorbance values at 1400-1900 nm (2 predictors) and at 1930 nm (1 predictor) generated equally good R^2 values (0.94 and 0.93, respectively) and low SEP values (0.84799% and 1.0245%, respectively) compared to all other models. These results suggested that the absorbance values at 1400-1900 nm and at 1930 nm were strong predictors of litter moisture and can be used independently for developing calibration equations to estimate litter moisture content.

5.2 INTRODUCTION

Optimal use of poultry litter as a fertilizer requires accurate knowledge of its physical and chemical properties for proper land application. Environmental issues in the past due to over-application of litter have focused research efforts on how to manage and apply litter more efficiently. Efficiency of application is measured by the accuracy and uniformity of spread in the field. For litter, maintaining uniformity of application is challenging due to high inherent variability in its physical properties. Moisture content and bulk density are two of the important properties that influence the performance of spreader used for applying litter. Litter density is an important setup parameter within a spreader rate controller that is used to manage conveyor mass flow. High moisture variability can produce density variation within litter and thereby could affect field application by generating off-rate errors. Therefore, real-time moisture content or density estimation during application could help maintain accurate metering and distribution by updating density values within the rate controller.

Rapid methods of moisture content measurement are used in agricultural materials due to their several advantages over conventional oven dry methods because they are quick, nondestructive, and can provide information about several material properties simultaneously. One such method is near infrared spectroscopy, which utilizes the infrared region (1000-2500 nm) of the electromagnetic spectrum to measure material reflectance and absorption properties. Near infrared spectroscopy is routinely used in processing and industrial facilities for quick analysis of forage, grains, and food products. This technique has been also applied for analysis of poultry manures, especially for determination of dry matter (moisture content) and nutrient contents. NIR spectroscopy has shown to be especially effective in measuring moisture due to strong absorbance of water in the infrared spectrum (Windham, 1988). The water O-H group and combination bands are stronger in NIR region of the spectrum compared to other regions of electromagnetic spectrum.

Reeves (2001 and 2002) evaluated NIR spectroscopy for determining poultry manure composition including its feasibility and limitations. They concluded that accurate calibrations for ammonium, organic and total N, and moisture content can be developed using a NIR spectra with coefficient of determination (R^2) values of 0.725, 0.894, 0.886 and 0.843, respectively. Ye et al. (2005) also reported that NIR spectroscopy can be effectively used for determining nutrient composition and quantity of certain minerals in manures. In a similar study, the feasibility of using NIR spectroscopy for rapid determination of composition of pig and manure slurries was investigated by Soronsen et al. (2007). Results indicated that NIR spectroscopy was suitable for rapid analysis of dry matter, N, and P in both cattle and pig manures. These researchers also reported that NIR spectroscopy can be effectively used for real-time moisture analysis in poultry litter. All these studies were focused on developing routine laboratory NIR calibrations for rapid determination of moisture, organic nutrients and minerals in animal and poultry manures. Most of the researchers have used Partial Least Squares Regression (PLSR) techniques on full NIR spectra to develop regression equations for estimating moisture content in litter. So far, no attempt has been made to develop simple regression equations using fewer wavelengths within the NIR region to determine litter moisture content.

The idea of real-time moisture measurement on a litter spreader would require use of a simple NIR sensor utilizing less number of wavelengths (possibly 2 or 3) instead of using full spectra (1000 nm – 2500 nm). Such a sensor would also be cost effective compared to expensive NIR spectrometers, which utilize full NIR region for analysis. Past research has shown that strong NIR absorption bands near 1400-1440 nm and 1900-1950 nm have been often applied for quantitative analysis of moisture content in food materials (Buning-Pfaue, 2003). Sundaram et al. (2010) reported that absorption bands at 1434 and 1920 nm were strongly related to moisture content in peanuts. These results suggest that strong absorption bands at certain wavelengths could be used for moisture measurement in poultry litter as well. Therefore, this study evaluates NIR spectroscopy for litter moisture measurement by determining wavelengths strongly related to moisture content. The research reported here investigates NIR technology as a means to meet the challenge of predicting litter moisture in real time with simple linear models using fewer wavelengths. The feasibility of this technology was evaluated through calibration development and verification of the regression models.

5.3 Sub-Objectives

The objectives of this study were to: (1) to collect NIR spectra measurements for poultry litter at different moisture contents and establish absorption bands or wavelengths strongly related to litter moisture, (2) to develop multiple linear regression models to predict the moisture content of broiler litter using NIR measurements at selected wavelengths, and (3) to validate the developed calibration models with litter samples and thereby evaluate their predictability performance.

5.4 Methodology

A load of bulk broiler litter (50 kg) was acquired and sealed in a plastic container. Ten random samples were collected and placed in sealed bags to determine mean moisture content and bulk density for the litter. Further another ten, 3-kg samples from the bulk litter were measured out and placed in small, air tight containers. The moisture content of these ten samples was altered by either drying or adding water to achieve the target moisture contents of 16%, 19%, 22%, 25%, 28%, 31%, 34%, 37%, 40% and 43% (w.b.) and set for 48 hours. These litter samples at 10 different moisture levels formed the calibration set for collecting NIR measurements in this study. The validation set consisted of 15 litter samples acquired from different production houses in north Alabama. These samples contained different levels of moisture content as well as physical variability (particle size and shape). The moisture content for each sample was determined by using standard oven method (*ASAE Standards*, 2003) and used as the reference moisture content during validation. Table 5.1 summarizes the moisture content data for the calibration and validation litter samples.

Table 5.1. Mean moisture content and standard deviation for the calibration and validation litter samples.

	Calibration		Validation	
	Actual Moisture Content (%)		Actual Moisture Content (%)	
Sample No.	Mean	Std. Dev.	Mean	Std. Dev.
1	16.2	0.3	17.4	0.3
2	19.3	0.2	19.1	0.6
3	22.1	0.2	20.0	0.3
4	25.2	0.2	21.0	0.6
5	28.3	0.2	21.1	0.3
6	31.4	0.1	22.8	0.5
7	34.3	0.3	23.4	0.4
8	37.0	0.2	24.1	0.4
9	40.4	0.2	24.5	0.9
10	42.9	0.1	24.8	0.7
11			27.2	0.8
12			27.3	0.7
13			27.4	0.6
14			28.6	0.5
15			28.8	0.5

5.4.1 Data Collection

NIR spectral measurements were made using a FT-NIR Spectrometer (Model: Spectrum 100N) (Perkin Elmer, Waltham, MA) (Figure 4.2). Spectral data were collected using software Spectrum^{TM} Ver. 6.31.0132 (Perkin Elmer, Waltham, MA) in .SPC format over the wavelength range between 1200 and 2200 nm. Each sample consisted of 25g – 30g of litter placed on a glass petridish over the NIR light source and covered with a cap. NIR radiation was directed through the sample and reflected light was collected for obtaining spectral data. The petridish containing the sample was continuously rotated, using spinner option within the spectrometer, during spectral measurements. This allowed spectral measurements at multiple points during the rotation for each sample. Three replications of each sample were performed for a total of 30 tests. The spectral data in was exported to MS Excel for data analysis.

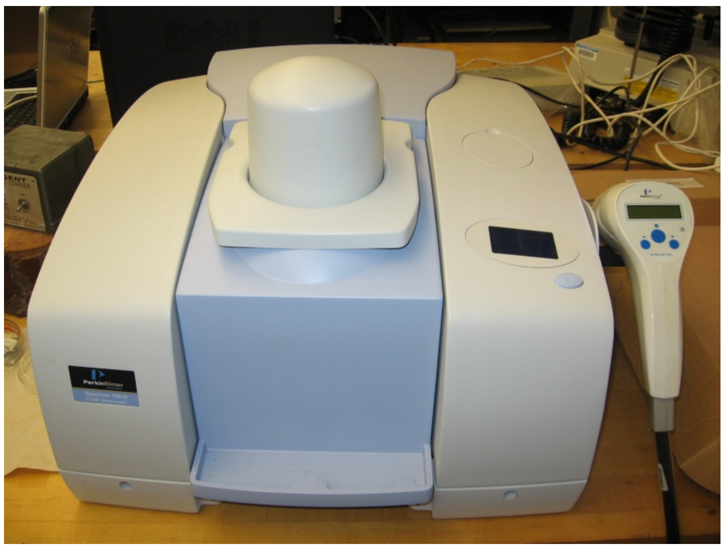


Figure 5.1. FT-NIR spectrometer used for collecting spectral data of broiler litter.

5.4.2 DATA ANALYSIS

NIR spectral data was analyzed using multivariate data analysis software (Unscrambler Version 10.2, CAMO Software Incorporation, Woodbridge, NJ) and SAS (Statistical Analysis Software Institute Inc., NC). Absorption values of the spectra at wavelengths between 1200 nm and 2200 nm at 0.5 nm intervals were taken as independent variables and the MC of the sample as the dependent variable for the analysis. Partial Least Squares (PLS), Principal Component Analysis (PCA) and SAS analysis was performed on the absorption data to determine the wavelengths that were strongly related to moisture content. The 'PROC REG' procedure along with ‘SELECTION’ statement in SAS software was used to select the best combination of two, three and four wavelengths for developing regression models. Calibration models were developed using the selected wavelengths in order to estimate litter moisture content. The best calibration models were identified based on the standard error of calibration (SEC), root mean square error of calibration (RMSEC) and coefficient of determination (R^2) values obtained from the data analysis results.

The selected models were used to predict litter MC for the validation set. The goodness-of-fit of the validation data set was evaluated based on the standard error of prediction (SEP) obtained by comparing the reference values determined by the standard oven method with those predicted by the models while computing the root mean square error of prediction (RMSEP), bias and coefficient of determination (R^2) values. Also, predicted values were plotted against the actual reference moisture values for comparison.

5.5 Results and Discussion

Figure 5.2 presents the averaged NIR absorption spectra of the broiler litter at ten different moisture contents. The average spectra at different moisture levels had similar shape, but different magnitude. The observed trend was that the magnitude of the overall average spectra increased with increase in moisture content. Peaks in the spectra occurred within the same wavelength bands (1400-1440 nm and 1900-1950 nm) for different moisture contents and represented high absorption of near-infrared energy within these regions. These strong absorption bands near 1400-1440 nm and 1900-1950 nm regions are related to the O-H stretch overtone bond and O-H bond of water, respectively (Sundaram et al., 2010).

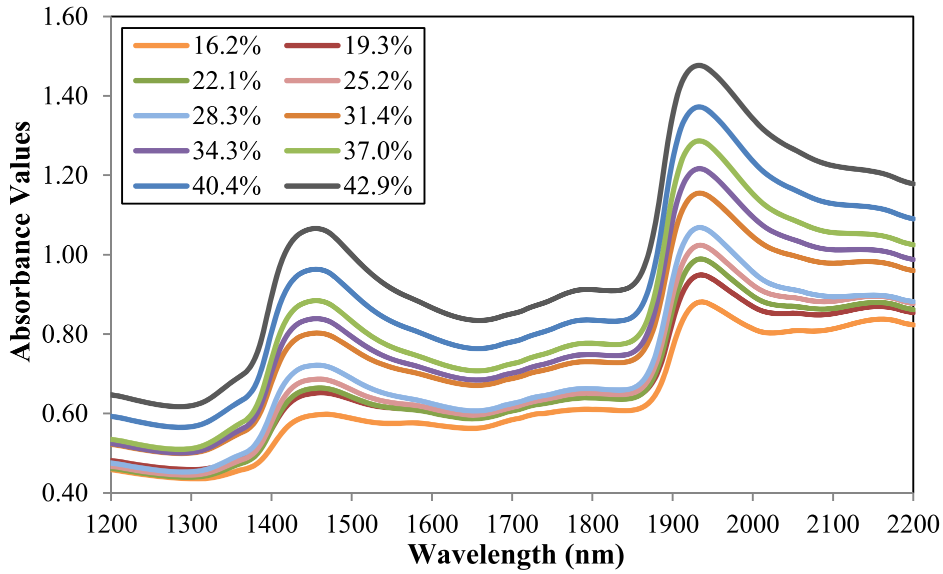


Figure 5.2. Averaged NIR absorption spectra of the broiler litter at different moisture contents.

5.5.1 PLS ANALYSIS

Figure 5.3 illustrates the regression coefficients of the partial least squares regression model. The absorbance values at the wavelengths over the range of 1200 nm to 2200 nm were used to develop this model. The regression coefficients for the model were obtained from both positive and negative absorption peaks (Figure 5.3). These data indicate that the peaks ranging between 1400-1440 nm and 1900-1950 nm contributed significantly to the regression coefficients of the equation. Similar results were observed in the Principal Component Analysis performed on the spectral data (Appendix J: Section J.4). This result can be attributed to the fact that these wavelengths are the strong absorption bands of water molecules. Changes in absorption bands near 1400 nm and 1900 nm regions are caused by the presence of water and have been often applied for analyzing moisture content in agricultural materials such as peanuts (Sundaram et al. 2010). Since the absorption bands at 1400-1440 nm and 1900-1950 nm regions for broiler litter also produced strong relationships with moisture content, the absorbance values in these regions were used for estimating the moisture content of litter. Further, the absorbance values within these wavelengths at 10 nm intervals were selected and used for developing multiple linear regression models. The selected wavelengths along with the nomenclature used for the absorbance value at each wavelength for developing the regression models are presented in Table 5.2.

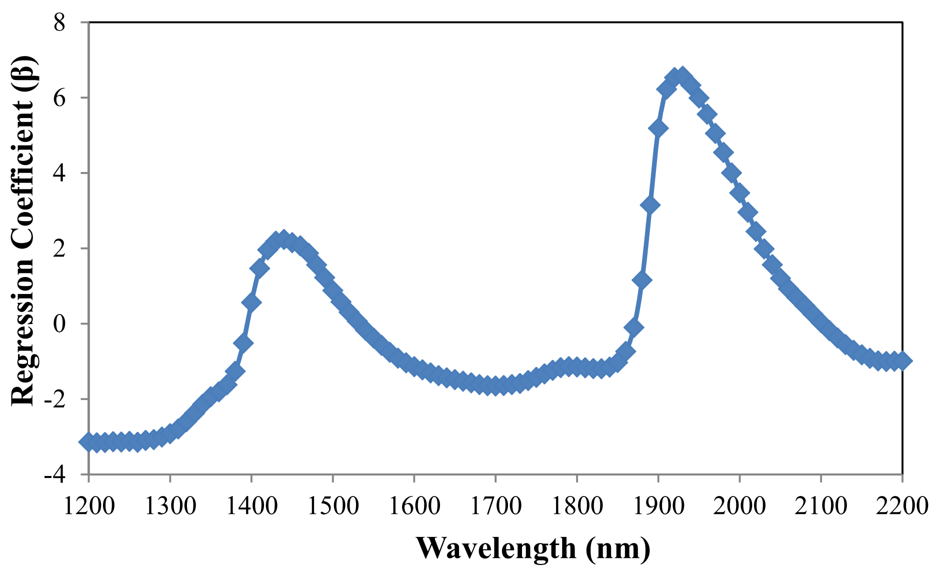


Figure 5.3. Regression coefficients of the PLS model for estimating litter moisture.

Table 5.2. Selected wavelengths and nomenclature used for absorbance values at these wavelengths.

Nomenclature (Absorbance Value)	M1	M2	M3	M4	M5	N1	N2	N3	N4	N5	N6
Wavelength (nm)	1400	1410	1420	1430	1440	1900	1910	1920	1930	1940	1950

5.5.2 LINEAR REGRESSION MODELS

The absorbance values at different combinations (one, two, three and four within each band, 1400-1440 nm and 1900-1950 nm) of selected wavelengths were used as the predicting variables and moisture content as the response for developing regression models. The combinations were chosen to determine a few strong predictors within these regions that can be independently used for moisture estimation in litter. Further, five best models for each combination were selected based on highest R^2 values, and lowest SEC and RMSEC values. The regression model with all eleven predictors was also selected to compare performance to other models relative to this model.

Table 5.3 presents the fitness measures of the calibration models obtained using absorbance values at selected wavelengths for calibration litter samples. High coefficient of determination (R^2) values of 0.99 was observed for the Models 1 through 16 demonstrating strong correlation between the absorbance and actual moisture content values for the litter samples. Regression models 17 through 21 (one predictor) also generated a strong linear relationship (R^2 = 0.97), but these relationships were lower compared to other models. While the lowest SEC and RMSEC values were obtained for Model 1 (11 predictors), the largest error values were produced by Model 21 (1 predictor). The SEC and RMSEC error increased from 0.3836% and 0.3771% to 1.4456% and 1.4212%, respectively with decrease in number of predictors from 11 to 1. Models 2 through 6 (4 predictors) and Models 7 through 11 (3 predictors) generated similar low calibration errors (SEC and RMSEC) ranging from 0.4551% to 0.4950%. The calibration errors produced by Model 17-21 (1 predictor) were all greater than 1.35% indicating less calibration accuracy of these models.

Predictors N4 and N5 corresponding to absorbance values at 1930 and 1940 nm, respectively contributed significantly to all the regression models signifying a strong relationship to litter moisture content. Though the calibration accuracy of the models reduced slightly with decrease in number of predictors, the models were still comparable. Therefore, all these models were considered as good calibration models for predicting moisture content in the validation litter samples.

Table 5.3. Fitness measures of the regression models for calibration litter samples.

Model	No. of Predictors	Predictors	R^2	SEC (% MC)	RMSEC (% MC)
1	11	M1 M2 M3 M4 M5 N1 N2 N3 N4 N5 N6	0.99	0.3836	0.3771
2	4	M1 N1 N4 N5	0.99	0.4551	0.4474
3	4	M1 N2 N4 N5	0.99	0.4586	0.4509
4	4	M3 N2 N4 N5	0.99	0.4588	0.4511
5	4	M4 N2 N4 N5	0.99	0.4600	0.4523
6	4	M2 N1 N4 N5	0.99	0.4604	0.4526
7	3	M2 N4 N5	0.99	0.4942	0.4859
8	3	M3 N4 N5	0.99	0.4943	0.4860
9	3	M4 N4 N5	0.99	0.4945	0.4862
10	3	M1 N4 N5	0.99	0.4945	0.4863
11	3	M5 N4 N5	0.99	0.4950	0.4867
12	2	M1 N2	0.99	0.9671	0.9509
13	2	M1 N1	0.99	0.9744	0.9581
14	2	M5 N2	0.99	0.9948	0.9781
15	2	M2 N2	0.99	1.0045	0.9877
16	2	M1 N3	0.99	1.0048	0.9879
17	1	N4	0.97	1.3813	1.3580
18	1	N3	0.97	1.3863	1.3630
19	1	N5	0.97	1.4094	1.3857
20	1	N2	0.97	1.4219	1.3980
21	1	N6	0.97	1.4456	1.4212

5.5.3 VALIDATION

Table 5.4 presents the fitness measures of the regression models obtained using the absorbance values at selected wavelengths for the validation litter samples. The models showed a good relationship between predicted and actual moisture values (R^2 = 0.87- 0.95). The SEP values for all the models were greater than 1% MC, except for Model 1 with SEP values less than 1% MC. While the RMSEP values for the Models 2-6 were less than 1.55%, the RMSEP values for the Models 7 through 21 were within 1.7% to 2.3% indicating high errors in the predicted moisture values for the litter samples. These errors occurred due to high bias in the predicted values for all these models. This bias was produced because of the difference in physical variability (particle size and shape) between the calibration and validation litter samples. As expected, Model 1 provided the best results with highest R^2 value of 0.95, and lowest SEP and RMSEP values of 0.8166% and 0.9957%, respectively. Next to that were the Models 2-6 with 4 predictors, which produced high R^2 values (0.90-0.91), and SEP and RMSEP values within 1.04% to 1.55%. Models 7-21 also performed well by producing results comparable to other models.

Table 5.4. Fitness measures of the models for validation litter samples.

Model	No. of Predictors	Predictors	R^2	SEP (% MC)	RMSEP (% MC)
1	11	M1 M2 M3 M4 M5 N1 N2 N3 N4 N5 N6	0.95	0.8166	0.9957
2	4	M1 N1 N4 N5	0.91	1.0594	1.4802
3	4	M1 N2 N4 N5	0.92	1.0407	1.5984
4	4	M3 N2 N4 N5	0.91	1.0977	1.4514
5	4	M4 N2 N4 N5	0.91	1.3119	1.4499
6	4	M2 N1 N4 N5	0.90	1.1237	1.5499
7	3	M2 N4 N5	0.87	1.3547	2.9335
8	3	M3 N4 N5	0.87	1.3524	2.9457
9	3	M4 N4 N5	0.87	1.3505	2.9594
10	3	M1 N4 N5	0.87	1.3496	2.9684
11	3	M5 N4 N5	0.87	1.3516	2.9263
12	2	M1 N2	0.94	0.8934	1.8418
13	2	M1 N1	0.94	0.8479	1.2961
14	2	M5 N2	0.94	0.9767	1.2701
15	2	M2 N2	0.94	0.9247	1.7594
16	2	M1 N3	0.94	0.9621	2.1741
17	1	N4	0.93	1.0245	2.4816
18	1	N3	0.93	1.0341	2.4301
19	1	N5	0.93	1.0310	2.4792
20	1	N2	0.93	1.0807	2.3240
21	1	N6	0.93	1.0516	2.4387

The best model within each combination group of predictors was selected based on lowest SEP and RMSEP values, and highest R^2 value (Table 5.5). Model with 2 predictors M1 and N1 (absorbance values at 1400 nm and 1900 nm, respectively) had the lowest SEP value of

0.8479% and a high RMSEP value of 1.2961%. While the model with N4 predictor (absorbance values at 1930 nm) generated the R^2 value of 0.93, the model with M2, N4 and N5 predictors (absorbance values at 1920, 1930 and 1940 nm, respectively) produced the lowest R^2 value of 0.87. Since three of four selected models had predictor N4 in the regression equation, this indicated that the absorbance value at 1930 nm (N4) had the strongest relationship with the litter moisture content. Also, the lowest SEC value for the model with M1 and N1 suggested that the absorbance values at 1400 (M1) and 1900 nm (N1) were strong predictors of moisture content in litter and predicted moisture content in the validation samples with reasonable accuracy (<1.5%).

Table 5.5. Fitness measures for the best regression model within each combination.

No. of Predictors	Predictors	R^2	SEP (% MC)	RMSEP (% MC)
4	M1 N2 N4 N5	0.92	1.0407	1.5984
3	M1 N4 N5	0.87	1.3400	2.7300
2	M1 N1	0.94	0.8479	1.2961
1	N4	0.93	1.0245	2.4816

Table 5.6 presents the values of regression coefficients for the best selected model within each combination group. The negative sign of regression coefficient represents the inverse relationship of the predictor with litter moisture. It was observed that the absorbance values for 1400 and 1940 nm wavelengths (predictors M1 and N5, respectively) has a negative contribution in the regression equations for predicting litter moisture, whereas the absorbance values at 1900, 1910, 1930 and 1940 nm has a positive contribution in the equation.

Table 5.6. Regression coefficients for the selected regression models.

No. of		Intercept	Coefficients			
Predictors	Predictors	$\beta 0$	β_1	β_2	β_3	β_4
4	M1 N2 N4 N5	5.3	-46.7	261.4	1439.5	-1641.3
3	M1 N4 N5	-5.1	-5.8	2092.1	-2066.9	
2	M1 N1	-15.7	-109.9	116.6		
1	N4	-22.5	45.7			

Graphical comparisons between the predicted moisture values using selected models and actual reference moisture values are provided in Figure 5.4. Regression lines between the predicted and actual moisture content values showed a good fit with 1:1 (45^o) line with R^2 greater than 0.87 for all the models. For an ideal fit, the slope and intercept of a regression line between predicted and actual values should be equal to 1 and 0, respectively. The slope of the regression lines for all the models was not significantly different from one (p-value>0.05), except for model with N4 predictor. For all the models, the predicted values were positively skewed (above the 1:1 line), which relates to high bias values produced by these models. This bias can be removed by adding a constant factor to the final regression model which would further improve the prediction accuracy by reducing the RMSEP value. The intercept values of all the regression lines were significantly different (p-value<0.0001) from zero. The intercept value increased from 2.2814 to 6.522 with decrease in number of predictors from 4 to 1, respectively.

In comparison, all 4 calibration models with 1 to 4 predictors performed well based on validation results. The data suggested that the absorbance values at 1930 nm or at 1400-1900 nm combined, can be independently used for estimating litter moisture with suitable calibration models. A simple, low cost NIR instrument utilizing these specific wavelengths can be developed for predicting litter moisture. This instrument will offer rapid and real-time moisture measurements of broiler litter. Further, single calibration equation can be developed for this NIR instrument and could be used for estimating moisture in different types of broiler litter.

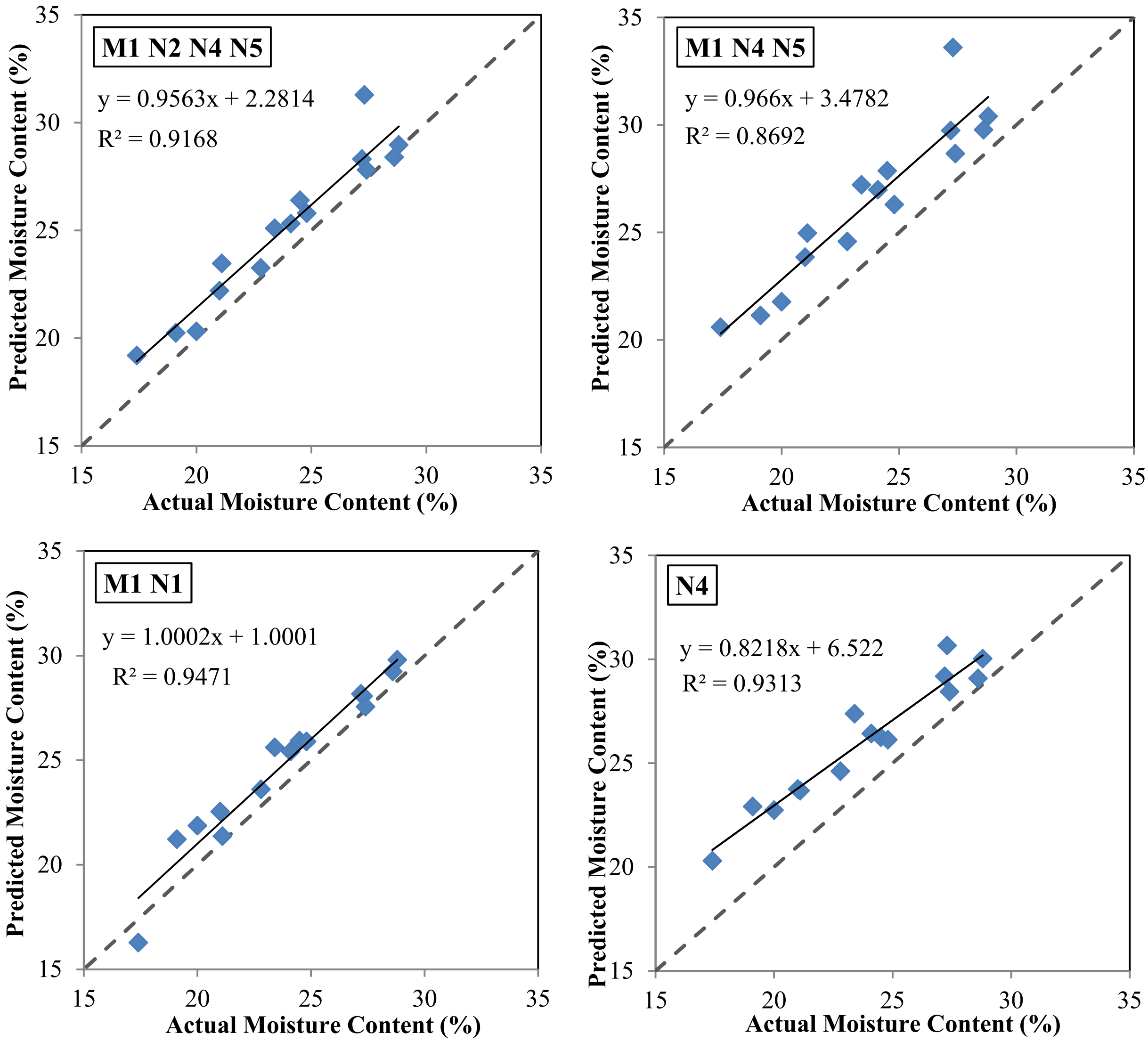


Figure 5.4. Comparison of predicted and actual moisture values for validation litter samples.

5.6 Summary

The NIR spectral measurements between 1200-2200 nm for broiler litter samples at ten different moisture contents was collected and analyzed to determine the wavelength regions highly correlated to moisture content. Initial results showed that the spectra magnitude increased with increase in moisture content of litter samples. High absorption peaks occurred near 1400-1440 nm and 1900-1950 nm in the spectra. The large regression coefficients in the 1400-1440 nm and 1900-1950 nm regions for the PLS regression model indicated the strong relationship of absorbance bands in these regions with moisture content in the litter.

Twenty one calibration models using absorbance values as predictors at different wavelength combinations (one, two, three, four and eleven wavelengths) within 1400-1440 nm and 1900-1950 nm regions were selected. All the models produced high R^2 values of 0.97-0.99 indicating strong relationship between the absorbance and moisture values. The SEC and RMSEC values increased from lowest of 0.3836% and 0.3771% MC, respectively for model with all 11 predictors to highest of 1.4456% and 1.4212% MC, respectively for model with 1 predictor.

Validation of the models also produced good R^2 values from 0.87 to 0.95 for all the models. The SEP and RMSEP values for most of the models were greater than 1%, except for model with 11 predictors with SEP and RMSEP values less than 1%. The best model within each combination group was selected based on high R^2 and low error values. The model using absorbance values at 1930 nm and at 1400 -1900 nm as the predictors produced the highest R^2 value of 0.93 and 0.94, respectively and lowest SEP values of 1.0245% and 0.8479% MC, respectively.

Overall, the results indicated that the absorbance values at 1930 nm or at 1400 nm plus 1900 nm can be used independently for predicting litter moisture by developing a suitable calibration model. The idea of measuring real-time litter moisture on a litter spreader would require a development of a simple, low cost NIR sensor utilizing these specific wavelengths to measure absorbance values corresponding to moisture content in litter. In future, moisture information could be used within spreader rate controller for better metering and distribution control.

CHAPTER SIX

SUMMARY AND DISCUSSION

The perspective about poultry litter over the past decades has considerably changed as viewing it as a waste product to utilizing it as a reliable nutrient source to meet soil or crop fertility requirements. During this same time, the equipment and technology for land application of litter has also undergone considerable improvement. The environmental issues related to litter application in the past have led researchers and environment agencies to develop better management practices (BMP's) along with using advanced technology for efficient use of litter. Introduction of rate controllers and guidance systems and on application equipment has improved control and management of application rates during field operation. As environmental regulations regarding litter use become stricter, knowledge and the ability to achieve uniform distribution needs to be more continuously maintained to reduce possible over-application risks. In this pursuit of improving spread distribution and increasing efficiency, technology will play a major role to meet current and future requirements placed on managing litter. When trying to evaluate application and distribution of litter, knowledge of physical and chemical properties is important. The physical properties of litter are highly variable as outlined in this thesis. This high variability in the physical flow properties of litter has a direct impact upon the performance of flow control and the discharge system for land application equipment. The ability to measure properties such as moisture content and bulk density on-the-go may provide the feedback to accurately meter and uniformly distribute litter.

6.1 Litter Moisture Content and Bulk Density

Moisture content and bulk density are two important parameters that influence litter application. The performance of conveyance and distribution system of a typical spinner-disc spreader is influenced by the high variability in the litter properties. The discharge rate of the spreader is directly related to bulk density of the litter, as the basis of the delivery system is based on the volume of material being spread. During application, density is used as a setup parameter in a rate controller and used to calculate the conveyor mass flow for maintaining the target rate. The results reported in this thesis indicated that litter density can affect spreader performance by generating off-rate errors higher than ±15%. The incorrect density values within the spreader rate controller affected the conveyor mass flow, thereby impacting application rate. The change in conveyor mass flow was also reflected in the distribution patterns for the litter. Knowledge of the correct density value for litter means better control and metering of mass flow. The importance of using the correct density value within rate controller was suggested to maintain accurate metering and uniform distribution during application.

Determination of right moisture content for litter is also very critical along with right density value for accurate field application. Moisture content determines the amount of dry mass present in the litter. Further, N-P-K rates are directly related to actual dry mass applied in the field during application. Dry mass can vary between litter sources and batches depending upon the variability in moisture content, particle size and shape. Table 6.1 shows an example illustrating difference between the dry mass rates for two broiler litter sources (A and B) with different moisture content and density values. Same spreader settings including a density value of 416.5 kg/m^3 was used in the rate controller for both litter types (Litter A and B). This value was the actual density for litter A and an incorrect density value for litter B. Therefore, the actual density value for litter B was not accounted in the rate controller. Based on the actual moisture content (32% and 28% for litter A and B, respectively) of each litter, actual dry mass rates were calculated from the total mass of litter conveyed per revolution (discharge rate). It was noticed that the percentage difference between the dry mass rates for litter A and B was greater than 20%. Theoretically, all other spreader and controller settings being constant, dry mass rates for both litter types should be same in order to meet the target application rate. These rates differed because of the difference in moisture content and density values between the litter sources. The percentage difference between the dry mass rates for litter A and B decreased to less than 6% when actual density value of litter B (480.6 kg/m^3) was accounted for in the rate controller. This suggested that density variations among the litter sources and within the batch should be accounted for within the rate controller to maintain dry mass rates in the field. Further, determination and knowledge of the right moisture content is important to determine the actual dry matter content of the litter and thereby dry mass rates.

Table 6.1. Example illustrating difference in dry mass (0% MC) rates for litter A and B at the same spreader settings.

Dry Mass Rate (kg/ha)			Dry Mass Rate (kg/ha)		
(416.5 kg/m^3)			(416.5 kg/m^3)	(480.6 kg/m^3)	
Litter A	Litter B	Percent Diff. (%)[a]	Litter A	Litter B	Percent Diff. (%)[a]
1191	1452	21.9	1191	1200	0.7
2291	2923	27.6	2291	2424	5.8
2281	2875	26.0	2281	2363	3.6
4483	5710	27.4	4483	4737	5.7

a.) Percentage diff. (%) is calculated as ((dry mass rate of litter B – dry mass rate of litter A)/dry mass rate of litter A)*100

As outlined in this thesis, large physical variability can exist in poultry litter depending on the type of management, feeding systems and storage conditions. Due to this inherent variability, moisture and density variations can exist within a load making it difficult to use one accurate density value within the rate controller. The density variations can be due to moisture variability within the litter since density is moisture dependent. The results presented in this thesis indicated a linear relationship ($R^2 = 0.99$) between moisture content and bulk density of broiler litter (Figure 6.1). Dependence of bulk density on moisture content for litter has also been reported in the past studies (Malone et al., 1992; Glancey and Hoffman, 1996; Thirion et al., 1998). Therefore, it is believed that the density values within a load can be determined indirectly from moisture information. Real-time moisture information can be used to update density values within the rate controller with the help of a proper moisture-density calibration curve. Also, the real-time moisture values can be used to calculate the actual dry litter mass being applied in the field. Further, if N-P-K content of a litter source is known, N-P-K rates can be better managed using real-time dry mass during application. Therefore, the idea of real-time moisture measurement in broiler litter was proposed as an approach towards developing technology for improving litter distribution.

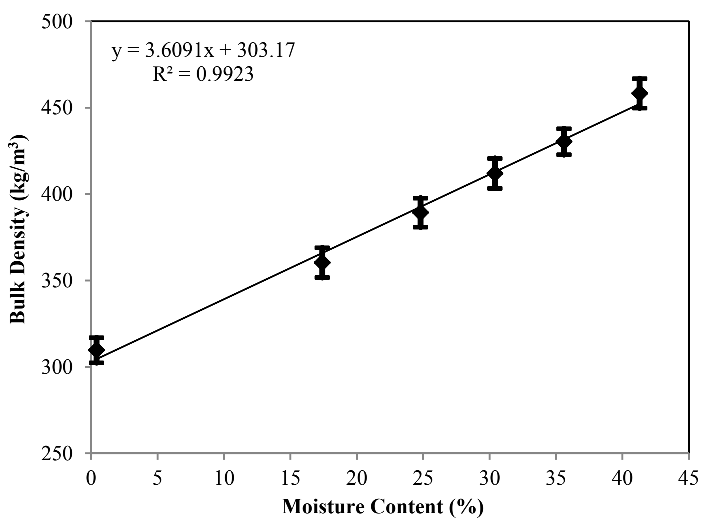


Figure 6.1. Moisture and bulk density relationship for broiler litter A (bars represent the standard deviation at each moisture content).

Information on litter moisture is also important due to other problems related to litter application using a spinner-disc spreader. The high moisture content in litter often leads to buildup on spreader components. Litter buildup on spinner-discs and vanes (Figure 6.2) can affect litter distribution by influencing the flow of material on the discs and along the vanes. The dimensions and shape of spinner-discs and vanes are designed in order to achieve near uniform distribution during application. Buildup on discs and vanes can change material flow thereby impacting distribution. Litter buildup can also cause problems of corrosion on spinner-discs and other spreader parts if not cleaned properly after application.

Figure 6.2. Illustration of litter buildup on spinner-discs and vanes.

Compressibility is another physical property dependent on the moisture content of litter. Litter compressibility creates another challenge from a metering perspective for application. High moisture content represents more mass of litter in the spreader hopper. The compressibility due to litter weight in the hopper can change the actual density (working density) of litter on the conveyor, which would be different from the bulk density value used in the rate controller. This difference can result in more litter mass per revolution conveyed out of the hopper. More litter mass per revolution will be reflected in higher metering and distribution errors. This problem again indicates the importance of knowing correct moisture content and density for the litter being spread.

With more research focused on litter moisture content in the future, a moisture range (like 20%-30%) can be determined and specified for efficient litter application using spinner-disc spreaders. This moisture range can be stated and regulated along with the best management practices for improving litter application. Further, the incorporation of real-time moisture measurement technology would help in meeting these moisture range recommendations along with providing density feedback to spreader rate controller for better application control on spinner spreaders.

6.2 FEASIBLE TECHNOLOGY FOR MOISTURE MEASUREMENT

The impact of physical variability on litter application can be reduced by inclusion of real-time moisture sensing technology on a litter spreader to make better spreading decisions as well as managing rates to account for density variability. Since litter density is dependent on moisture content, the idea of using density values indirectly from real-time moisture information within a rate controller was proposed in this thesis. The feasibility of a capacitance type moisture sensor for measuring real-time moisture content in broiler litter was evaluated. Data indicated that the output voltage of the capacitance sensor increased with increase in litter moisture content and bulk density (Figure 7.2). The sensor response was close to linear at different density treatments before a cut-off voltage was reached (7.35 V). The operating range of the sensor decreased with increase in bulk density of litter, with 16%-31% MC being the largest possible measurement range at the loose bulk density. The 16%-31% MC is a common measuring range of this type of technology. It was also noted that air space or voids inside the housing affected the voltage output, since sensor output was related to dielectric constant of the sample plus air between the electrodes.

Based on the results, this sensor can be a good option for moisture measurement in broiler litter for static and routine laboratory procedures. However, the practical application of this sensor on a litter spreader is restricted by few limitations:

1. Sensor can only measure moisture content in broiler litter within 16% to 31% range. The measurement beyond 31% requires additional investigation to increase sensor operating range or use of some other device.
2. Litter density impacts the sensor output voltage and limits the operating moisture measurement range. Higher the bulk density, lower the operating moisture range of the sensor.
3. Sensor can be only used for contact-type moisture measurements. Maintaining continuous material-sensor contact for rapid moisture measurements would require constant litter flow through the sensor electrodes (plates), which would be hard to achieve considering large particle size variability found in broiler litter.
4. Presence of void spaces due to high particle size variability between the sensor electrodes (or housing) will affect sensor output and thereby provide inaccurate moisture measurements.
5. Litter flow problems can also occur due to large chunks getting stuck between the sensor electrodes possibly making sensor inoperative.
6. Material sticking to sensor electrodes due to high litter moisture can affect sensor performance and provide inaccurate moisture estimates.
7. Sensor should be clean all the time during operation. The dust generation due to dry litter can affect sensor performance by settling on electrodes.

8. Sensor performance can be affected by the disturbances due to spreader vibrations and other operational factors during litter application.

This sensor needs further development and evaluation for litter moisture measurement on a spreader, with major considerations of accounting for litter density and increasing the operating range to at least 40% MC. Since sensor output was responsive to density variations, future work can also be directed towards developing equations or indices for independently measuring both moisture and density with this sensor.

This thesis also presents evaluation of a NIR technique for moisture measurement in broiler litter. The main objective was to determine strong absorption wavelengths related to litter moisture within the NIR spectra. Results indicated that strong absorption bands near 1400-1400 nm and 1900-1950 nm related to litter moisture existed within the spectra. The calibration and validation models relating the absorbance values at 1400 plus 1900 nm and at 1930 nm to litter moisture content indicated high correlations (R^2 = 0.93) and low standard error of performance (SEP) values (0.8479% and 1.0245%, respectively). Moisture measurement using this sensor has merit over the capacitance-type sensor:

1. The sensor was able to measure the full moisture range (16%-43%) in broiler litter whereas the capacitance-type sensor was limited to between 16% and 31%.
2. The moisture readings determined using the NIR technique was density-independent. Litter density did not impact sensor performance unlike the capacitance sensor.

The potential of a NIR sensor for moisture measurement in broiler litter appears more promising than capacitance sensor. Between these two sensors, NIR sensor would be recommended because of its ability to provide rapid, nondestructive and density-independent moisture estimates. The application of this sensor on a litter spreader would require development of a simple, low cost sensor utilizing one or two strong absorption wavelengths for acquiring moisture information. The non-contact nature of this sensor also offers more flexible use compared to a contact type capacitor sensor. The non-contact operation would eliminate problems due to material sticking to sensor parts as well as other flow problems due to high particle size variability in litter. The NIR sensor can have few limitations as well for its use on a litter spreader. The sensor performance can be affected by the dust generation if litter is too dry during spreading. Also, the moisture measurement area of NIR sensor is less compared to capacitance type sensor since it utilizes single light beam to measure surface moisture content. However, NIR sensor still has more merits over capacitance sensor with its non-contact nature and rapid density-independent measurements without any major limitation. Overall, a NIR sensor has a good potential for litter moisture measurement on a litter spreader.

For the future, additional research needs to be conducted to evaluate other wavelength regions in electromagnetic spectrum (visible, IR, etc.) for density measurement in broiler litter. Strong absorption wavelengths related to litter density, if determined, could be used for predicting litter density. The possibility of predicting bulk density and moisture content with one sensor would be an added advantage for litter application. Development of such a sensor capable of providing both moisture and density information to a spreader rate controller would be an appropriate technology for improving litter application. However, this type of sensor must be cheap (preferably < $1000) in order to justify its use on a litter spreader. Also, the sensor should be able to provide density-independent moisture readings along with density values.

6.3 FEEDBACK TO A RATE CONTROLLER

With the development and use of an inline moisture and/or density sensor on a litter spreader, real-time moisture and density information can be provided to the rate controller as a secondary feedback (Figure 7.3). The moisture feedback information can be used to make better spreading decisions, whereas density feedback would help to update real-time density values within rate controller for better control and management of target application rates and distribution. The conveyor speed can be adjusted accordingly to account for density variations during application. In future, the density feedback can be also be used for making on-the-go rear gate adjustments to keep the volume of material constant. It can also be used for making other spreader hardware adjustments (such as spinner-disc speed and rear divider position) to improve litter distribution. The technology for cleaning of spinner-discs can also be developed in future to eliminate litter buildup problem due to high moisture during spreading. Real-time moisture information within a rate controller could be used with this technology for keeping the spinner-discs clean during application.

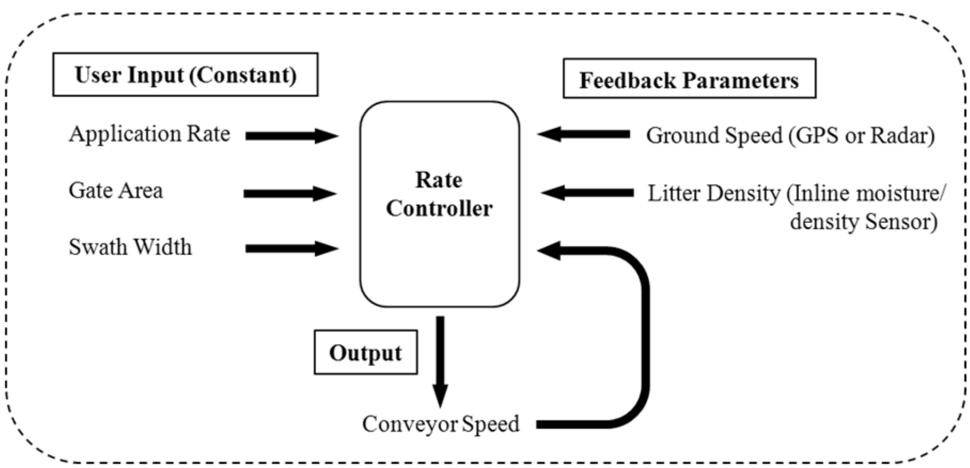


Figure 7.1. Diagram indicating user input and feedback parameters for a typical rate controller used on litter spreaders.

The research presented in this thesis is a step towards automation of control on litter spreaders. Improvement in technology on a litter spreader can offer real-time analysis of poultry litter for its more efficient use while minimizing environmental risks. As a step towards advancing technology, this research suggested the development of real-time moisture and/or density sensor on a litter spreader for improving litter application. In future, technology can be further improved to analyze real-time N-P-K content of the poultry litter along with moisture content and bulk density. Inclusion of real-time nutrient analysis of litter on a spreader will ensure increased nutrient application accuracy and distribution uniformity. Presently, due to operational errors associated with application equipment and other factors, the acceptable accuracy range for litter application is defined as within ±10% of the target rate. The technological advancement on a litter spreader in the future might help reduce this range to ±5% or less thereby improving application accuracy and uniformity of distribution.

CHAPTER SEVEN

CONCLUSIONS

7.1 CONCLUSIONS

Objective 1 focused on evaluating the influence of litter bulk density on metering and distribution of broiler litter when using a spinner-disc spreader. Results indicated that conveyor discharge rate (mass flow) errors were higher (>±15%) for incorrect density values used within the rate controller compared to lower rate errors (<±10%) for correct density values. Differences between dry mass rates (0% MC) for litter A and B were greater than ±20% when the actual density value for litter B was not accounted for in the spreader rate controller. The central peak of the "W" shaped single-pass patterns varied between the different density treatments due to change in actual conveyor mass flow onto the spinner-discs. The pattern peak increased with increase in actual conveyor flow. Comparison among standardized patterns exhibited differences between the patterns at correct and incorrect density treatments at a few transverse locations (-3.7 m to 3.7 m from spreader centerline) across the spread width. The change in conveyor mass flow due to incorrect density treatments generated some differences in the distribution patterns. Therefore, the use of correct density values within the spreader rate controller will be required in the future for accurate litter metering and distribution.

The second research objective investigated the feasibility of a capacitance type moisture sensor for measuring moisture content in broiler litter. Results concluded that litter density affected the sensor output voltage. The voltage response of the sensor was linear within the 16%-

31% moisture range depending on the density treatment used. The prediction models relating sensor output to litter moisture content provided high linear correlations (R^2 = 0.96-0.98) and low errors (<1%) suggesting high calibration accuracy linked to the models. Results for model validation also generated equally good correlations (R^2 = 0.90-0.94) and small prediction errors (<1.2%) indicating a strong relationship between the predicted and actual (reference) moisture values determined by the standard oven method. Overall, the capacitance sensor appears promising for real-time moisture sensing of broiler litter within the 16% to 31% range, but the effect of density on sensor performance must be accounted for in order to obtain accurate moisture estimates.

The final objective of this research focused on determining which absorption wavelengths within the NIR spectra would accurately estimate moisture content in broiler litter. Results indicated that strong absorption bands near 1400-1440 nm and 1900-1950 nm were highly related to litter moisture content. The calibration models developed using absorbance values within these regions to estimate litter moisture content provided high correlations (R^2 = 0.97-0.99). Validation results revealed that the models with absorbance values at 1930 nm and at 1400 nm plus 1900 nm produced the highest linear relationships (R^2 = 0.93 and 0.94, respectively) and lowest SEP values (1.0245% and 0.8479%, respectively). The results supported the idea of development of a simple NIR sensor utilizing one or two wavelengths for real-time moisture measurement of broiler litter.

In conclusion, metering and distribution of broiler litter using a typical spinner-disc spreader was impacted by density values used within a spreader rate controller. High rate errors and differences in distribution patterns due to incorrect density values highlighted the importance of using the correct density values within a rate controller. Real-time moisture and density information as a secondary feedback to a spreader rate controller was proposed to maintain acceptable litter application, especially for accurate metering. Both capacitance and NIR sensor techniques worked well for measuring real-time moisture content in broiler litter. While the NIR sensor operated within the full selected moisture range (16%-43%), the operating range for the capacitance sensor was limited to between 16% and 31%. A NIR sensor would be recommended for use on a litter spreader because of its wide moisture measurement range (16%-43%) along with ability to provide density-independent moisture readings. The idea of using this sensor on a litter spreader for inline moisture information is a viable option with proper sensor calibration and installation.

7.2 Opportunities for Future Research

Based on the results, additional research needs to be conducted to investigate the potential use of capacitance and NIR sensor on an actual litter spreader. Though capacitance type sensor has some limitations, additional testing can still be conducted to evaluate the sensor's operability on a litter spreader. Improved housing and installation equipment design would be needed to mount the sensor on the spreader. Housing should be designed to ensure proper sensor-material contact during litter flow to obtain accurate sensor output. Field testing is also required to evaluate the sensor performance during litter conveyance on a spreader and the effect of spreader vibrations on sensor output.

A simple NIR sensor utilizing 1930 nm or 1400 plus 1900 nm wavelengths can be fabricated for collecting absorption spectral information and thereby moisture estimation of broiler litter. Appendix C outlines a conceptual design for development of a simple, single or dual wavelength NIR sensor. The development of a single calibration equation would be needed to analyze the sensors ability to predict moisture in various sources of broiler litter. Field testing for evaluating sensor performance during litter conveyance and effect of other operating conditions on a litter spreader needs to be conducted. The potential of combining NIR with some other technology for measuring litter moisture content and density simultaneously needs to be evaluated and included in the calibration equation. A sensor capable of measuring litter moisture and density simultaneously is needed on a litter spreader to provide accurate and rapid density updates within rate controller.

Real-time density updates using the appropriate inline moisture and/or density sensing technology can be included within Spreader Control Software to make on-the-go mass flow adjustments to account for density variation within a load or pile. The density updates could also be used to make spinner-disc speed adjustments for maintaining acceptable distribution patterns during application. The spreader performance using real-time density values during litter application can be tested for metering and distribution errors.

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APPENDICES

APPENDIX A

DESIGN CONSTRAINTS FOR A MOISTURE SENSOR

A.1 Moisture Sensor Constraints for use on a Litter Spreader

1. **Economic:** Cheap (within $500-$1000).
2. **Accuracy:** Provide accurate measurements within ±1-2% moisture content (See Appendix B).
3. **Measurement Range:** Operate within 15% - 40% MC.
4. **Type of measurement:** Preferred non-intrusive or non-contact type sensor due to physical variability of litter.
5. **Response:** Provide rapid and real-time moisture measurements.
6. **Sampling frequency:** Preferably 10-15 moisture readings per minute.
7. **Durability:** Withstand the mechanical vibrations and other operating conditions during field application.
8. **Compatibility:** Compatible output for use with the rate controller software.
9. **Usability:** Easy to use, calibrate and setup.
10. **Installation:** Easy to install and uninstall on a litter spreader.

APPENDIX B

MOISTURE MEASUREMENT ACCURACY

B.1 MOISTURE MEASUREMENT ACCURACY NEEDED FOR ACCEPTABLE APPLICATION RATE

Table B.1 presents the mean moisture content and wet bulk density for clean out poultry litter reported by Malone et al. (1992). The data indicated that the moisture content and wet bulk density of clean out manure, on average, increased from 27% and 432 kg/m^3, respectively to 32% and 545 kg/m^3, respectively as the number of flocks grown in the house increased from a low of 1 to 6 flocks to a high of 13 to 18 flocks, respectively.

Table B.1. Mean moisture content and wet bulk density for clean out poultry litter (Malone et al. 1992).

No. of Flocks	Mean Moisture Content (%)	Mean Wet Bulk Density (kg/m$^{3)}$
1–6	27	432
13 –18	32	545

Table B.2 presents the theoretical application rates for poultry litter based on mean bulk density values (at two different moisture contents), assuming other spreader/controller settings as constant. The observed difference between the application rates at two different moisture contents (or bulk densities) is 26%, which is outside the ±10% acceptable limit for litter application. Considering linear relationship between moisture content and application rate, a ±5% increase in moisture content will result in ±26% increase in application rate. Similarly, increasing the moisture content by ±2.5% will exhibit ±13% increase in application rate. Therefore, the required accuracy of the sensor on a litter spreader should be within ±1-2% MC in order to maintain the application within ±10%.

Table B.2. Theoretical application rate for poultry litter based on mean moisture content and bulk density values.

Mean Moisture Content (%)	Mean Wet Bulk Density (kg/m^{3})	Theoretical Application Rate (kg/ha)	Percent increase in rate from 27% to 32% MC (%)
27	432	3495	26
32	545	4406	

The data presented here represents only one poultry litter source, reported by Malone et al. (1992). This data is used as an example to illustrate how large moisture and density variation can occur within the same litter source and how it can impact application rates in the field when applied using spinner-disc spreader. Generally, similar variation in moisture and density exists for other litter sources as well. Therefore, determination of moisture content within an accuracy range of ±1-2% MC becomes crucial on a litter spreader for maintaining acceptable application accuracy (±10%).

APPENDIX C

NEAR-INFRARED SENSOR SPECIFICATIONS

C.1 DESIGN SPECIFICATIONS FOR A SINGLE OR DUAL WAVELENGTH NIR SENSOR

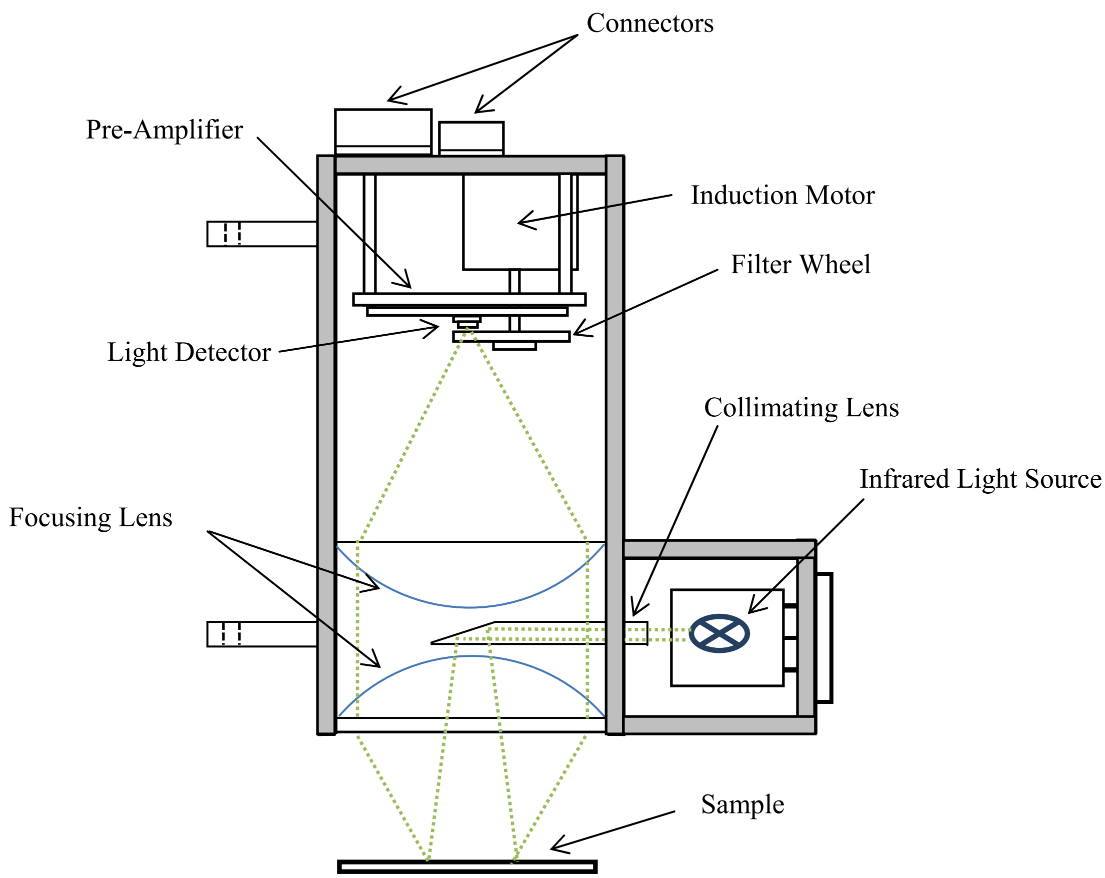

Figure C.1. Schematic diagram showing major components of a NIR sensor.

Table C.1. List of major components and their corresponding function for a NIR sensor.

Component	Function/Description
IR Light Source	Emits the near-infrared radiation at specific wavelength. Light from the light source enters the collimating lens.
Collimating Lens	Covert divergent beam of light into parallel path and focuses it on the sample to be analyzed.
Focusing Lens	Receives reflected light from the sample and focuses the reflected light onto the filter.
Filter Wheel	Restricts optical radiation to pre-determined wavelength regions. Various types of filters are available to restrict the radiation to certain wavelength regions.
Induction Motor	Rotates the filter wheel at the desired speed depending on the incident angle of the reflected light and type of spinning filter used.
Light Detector	Collects the specific radiation received from the filter wheel and converts the optical signal to a digital signal.
Pre-Amplifier	Removes the noise and amplifies the digital signal before sending it to connector.
Connectors	Contain multiple ports to transfer amplified digital signal to the connecting device (computer, tablet etc.)

Table C.2. Recommended components and their specification for fabrication of a single/dual wavelength NIR sensor.

Component	Specification
IR Light Source	LED (light emitting diode) containing Gallium Arsenide (GaAs). Suitable for emitting one or two specific wavelength bands. Low power requirement and long life expectancy.
Collimating Lens	Achromatic front surface mirror/lens (Aluminum coated). Relatively low cost compared to gold surfaced lens.
Focusing Lens	Spherical concave precision lens with flat rear surface and gold coating. High reflectance in the Near-Infrared region.
Filter Wheel	AOTF (Acoustic Optical Tuneable Filter) directed into a TeO_2 crystal. Operating wavelength range (1000-2000 nm). Adjustable intensity and gives narrow beam.
Induction Motor	3phase DC motor. Operating power requirements and rpm range dependent on filter wheel size and desired wavelength bands.
Light Detector	InSb/InAs (Indium Antimonide/Indium Aresenide). Wavelength range 700 – 2000 nm. Very high responsivity. High quality detector.
Pre-Amplifier	NIR Photodetector-Preamplifier (Opto Diode Corporation). High sensivity, large active area and low noise.
Connector	30-36 Pin standard connector. Digital input/output channels. Easy connectivity with portable data devices (laptop, tablet etc.)

APPENDIX D

TRACTOR AND SPREADER SPECIFICATIONS

D.1 John Deere Model 6420 Tractor

Figure D.1. John Deere 6420 agricultural tractor.

Tractor Power:	
PTO rated, kW:	70.3
Engine:	
Manufacturer:	John Deere
Fuel:	Diesel
Aspiration:	Turbocharger
Cylinders:	Turbocharger with intercooler
Displacement, L:	4
Rated Engine speed, RPM:	2300
Cooling:	liquid
Oil Capacity, L:	15.9
Hydraulic flow rate, LPM:	96
Type of Transmission	Infinitely Variable Transmission
Mechanical: MFWD	Yes
Guidance System:	Greenstar AutoTrac system using RTK

D.2 Chandler Equipment Company Litter and Shavings Spreader

Figure D.2. Chandler Equipment Co. litter spreader.

Figure D.3. Litter spreader rear gate, conveyor chain, flow divider and spinners.

Manufacturer:	Chandler Equipment Company, Gainesville, GA
Bed Length, cm:	360
Oil Capacity, L:	113.6
Tire Size:	12.5L × 15
Chain width, cm:	85.1
Spinner diameter, cm:	76.2
Max. gate height, cm:	34.9
Vane Height, cm:	7.6
Vane Length, cm:	27.9
Divider width, cm:	83.8
Divider Length, cm:	42.5
Divider Height, cm	11.4

D.2.1 HYDRAULIC SPINNER MOTORS

Figure D.4. Parker/Commercial Intertech hydraulic spinner motor.

Manufacturer:	Parker
Series#:	Commercial Intertech M-30
Part#:	400-C-201
Displacement, CI/REV:	7.8
Max pressure, PSI:	2000-3000

D.2.2 HYDRAULIC TANDEM CONVEYOR MOTORS

Figure D.5. Parker/Ross hydraulic conveyor motors.

Manufacturer:	Parker
Series#:	Ross MB120102AAAA
Part#:	400-R-106
Displacement, CI/REV:	6.1
Max Pressure, PSI:	2250-3000

D.2.3 HYDRAULIC PTO TANDEM PUMP

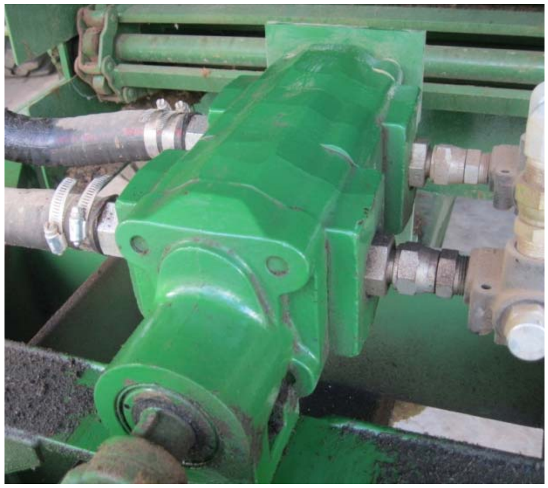

Figure D.6. Prince hydraulic PTO tandem pump.

Manufacturer:	Prince
Model#:	400-C-209
Displacement, CI/REV:	9.9
Flow rate, LPM:	81@ 500 PSI;79.5@1000, 1500 and 2000 PSI
Input Power, HP:	8.4@500 PSI; 16.1@1000 PSI; 23.8@1500 PSI; 32.1@2000 PSI
Max pressure, PSI:	2250
Speed rating, RPM:	1000

D.2.4 Electronically Adjustable Flow Control Valves

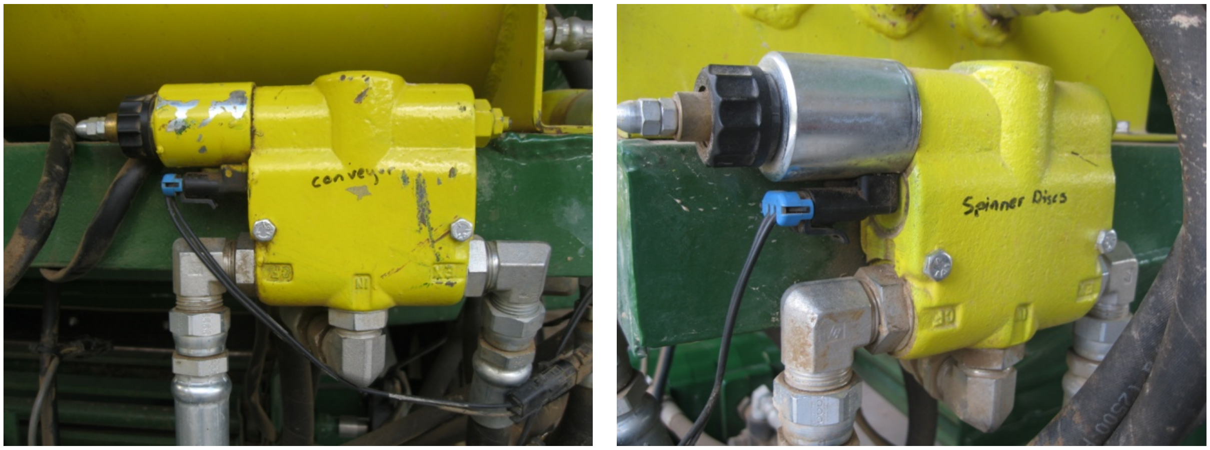

Figure D.7. Brand proportional hydraulic valves used for conveyor and spinner control.

Manufacturer:	Brand Hydraulics
Max pressure, PSI:	3000
Pulse frequency, Hz:	90 to 115
Spinner valve:	PWM
Part#:	400-1-313
Flow rate, LPM:	0 to 75.7
Conveyor Valve:	PWM
Part#:	400-3-313
Flow rate, LPM:	0 to 56.8

APPENDIX E

TOPCON PRECISION AG CONSOLE AND SENSORS

E.1 TOPCON PRECISION AG X20 CONSOLE

Figure E.1. Snapshot X20 console showing the main screen of the Spreader Control Software.

Console:	
Processor:	1 GHZ
Memory:	512 MB
Operating System:	Windows XP PRO SP2
Display Size:	213 mm (8.4 in.)
Solid State drive:	2 GB
Audio:	1.5 W stereo
Mounting bracket:	RAM mount
USB ports:	4 × USB 2.0
Serial RS232 ports:	4
PS2 ports:	2
VGA ports:	1
10/100 Basic T Ethernet port:	1
Spreader Control Software:	
Version:	1.48
Capabilities:	Variable-rate Application (VRA)

E.2 ELECTRONIC CONTROL UNIT

Figure E.2. Electronic Control Unit (ECU) used with a litter spreader.

Manufacturer:	Topcon Precision Ag
Operating Voltage, VDC:	12 to 24

E.3 INDUCTIVE PROXIMITY SENSORS

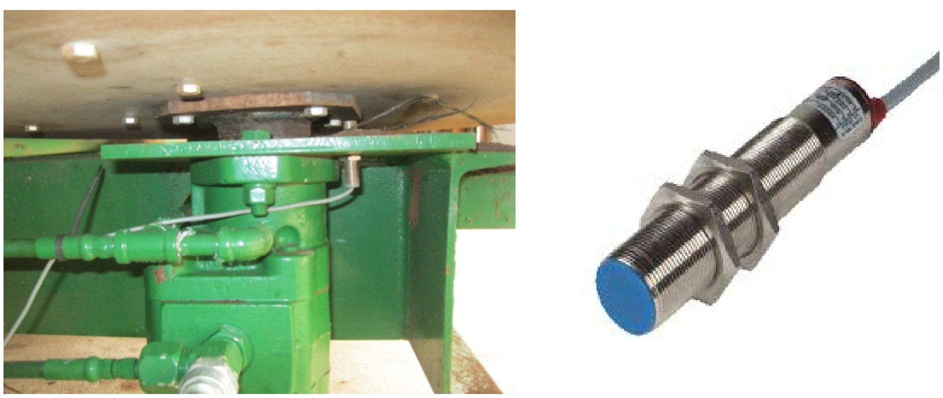

Figure E.3. Proximity sensor to monitor spinner-disc speed.

Manufacturer:	Automation Direct
Model#:	AE1-AN-4A
Type:	Unshielded
Sensing range, mm:	0 to 4
Logic:	NPN
Operating Voltage	10 to 30 VDC

E.4 DICKEY JOHN ENCODER

Figure E.4. Encoder to monitor conveyor speed.

Manufacturer:	Dickey-John Corporation
Model#:	46436-1170A
Type:	Application rate sensor
Output:	360 pulses per revolution
RPM range:	0 to 2500
Operating Voltage	12V

APPENDIX F

CONVEYOR DISCHARGE RATE DATA

F.1 Conveyor Discharge Rate Data for Individual Density Treatments

Table F.1. Discharge rate summary for 416.5 kg/m^3 density treatment (litter A).

Treatment ID	Rep	Controller Settings: Density (kg/m^3)	Gate Height (cm)	Target Rate (kg/ha)	Mean Discharge Rate (kg/rev): Theoretical	Actual	Error (%)
P	1	416.5	17.8	1743	25.1	25.4	1.2
	2	416.5	17.8	1743	25.1	23.6	-6.0
	3	416.5	17.8	1743	25.1	26.8	6.8
Q	1	416.5	17.8	3486	25.1	24.7	-1.6
	2	416.5	17.8	3486	25.1	21.0	-16.3
	3	416.5	17.8	3486	25.1	27.1	8.0
R	1	416.5	34.9	3424	49.4	53.4	8.1
	2	416.5	34.9	3424	49.4	45.8	-7.3
	3	416.5	34.9	3424	49.4	45.9	-7.1
S	1	416.5	34.9	6848	49.4	44.8	-9.3
	2	416.5	34.9	6848	49.4	47.3	-4.3
	3	416.5	34.9	6848	49.4	50.4	2.0

Table F.2. Discharge rate summary for 352.4 kg/m^3 density treatment (litter A).

Treatment ID	Rep	Controller Settings: Density (kg/m^3)	Gate Height (cm)	Target Rate (kg/ha)	Mean Discharge Rate (kg/rev): Theoretical	Actual	Error (%)
P1	1	352.4	17.8	1743	21.3	24.2	13.6
	2	352.4	17.8	1743	21.3	31.6	48.4
	3	352.4	17.8	1743	21.3	23.4	9.9
Q1	1	352.4	17.8	3486	21.3	23.7	11.3
	2	352.4	17.8	3486	21.3	24.8	16.4
	3	352.4	17.8	3486	21.3	26.0	22.1
R1	1	352.4	34.9	3424	41.8	54.8	31.1
	2	352.4	34.9	3424	41.8	48.5	16.0
	3	352.4	34.9	3424	41.8	46.0	10.0
S1	1	352.4	34.9	6848	41.8	48.4	15.8
	2	352.4	34.9	6848	41.8	45.7	9.3
	3	352.4	34.9	6848	41.8	47.6	13.9

Table F.3. Discharge rate summary for 480.6 kg/m^3 density treatment (litter B).

Treatment ID	Rep	Controller Settings: Density (kg/m^3)	Gate Height (cm)	Target Rate (kg/ha)	Mean Discharge Rate (kg/rev): Theoretical	Actual	Error (%)
E	1	480.6	17.8	1743	29.0	27.0	-6.9
	2	480.6	17.8	1743	29.0	28.7	-1.0
	3	480.6	17.8	1743	29.0	27.6	-4.8
F	1	480.6	17.8	3486	29.0	28.1	-3.1
	2	480.6	17.8	3486	29.0	28.5	-1.7
	3	480.6	17.8	3486	29.0	27.3	-5.9
G	1	480.6	34.9	3424	57.0	53.2	-6.7
	2	480.6	34.9	3424	57.0	54.3	-4.7
	3	480.6	34.9	3424	57.0	56.2	-1.4
H	1	480.6	34.9	6848	57.0	55.5	-2.6
	2	480.6	34.9	6848	57.0	52.8	-7.4
	3	480.6	34.9	6848	57.0	56.1	-1.6

Table F.4. Discharge rate summary for 416.5 kg/m^3 density treatment (litter B).

Treatment ID	Rep	Controller Settings: Density (kg/m^3)	Gate Height (cm)	Target Rate (kg/ha)	Mean Discharge Rate (kg/rev): Theoretical	Actual	Error (%)
E1	1	416.5	17.8	1743	25.1	28.9	15.1
	2	416.5	17.8	1743	25.1	27.8	10.8
	3	416.5	17.8	1743	25.1	30.6	21.9
F1	1	416.5	17.8	3486	25.1	28.3	12.7
	2	416.5	17.8	3486	25.1	30.4	21.1
	3	416.5	17.8	3486	25.1	29.1	15.9
G1	1	416.5	34.9	3424	49.4	58.6	18.6
	2	416.5	34.9	3424	49.4	55.3	11.9
	3	416.5	34.9	3424	49.4	58.8	19.0
H1	1	416.5	34.9	6848	49.4	54.6	10.5
	2	416.5	34.9	6848	49.4	57.2	15.8
	3	416.5	34.9	6848	49.4	59.6	20.6

Table F.5. Discharge rate summary for 544.6 kg/m^3 density treatment (litter B).

Treatment ID	Rep	Controller Settings: Density (kg/m^3)	Gate Height (cm)	Target Rate (kg/ha)	Mean Discharge Rate (kg/rev): Theoretical	Actual	Error (%)
E2	1	544.6	17.8	1743	32.9	27.8	-15.5
	2	544.6	17.8	1743	32.9	26.6	-19.1
	3	544.6	17.8	1743	32.9	28.8	-12.5
F2	1	544.6	17.8	3486	32.9	27.1	-17.6
	2	544.6	17.8	3486	32.9	27.7	-15.8
	3	544.6	17.8	3486	32.9	26.0	-21.0
G2	1	544.6	34.9	3424	64.6	56.4	-12.7
	2	544.6	34.9	3424	64.6	51.7	-20.0
	3	544.6	34.9	3424	64.6	56.1	-13.2
H2	1	544.6	34.9	6848	64.6	54.6	-15.5
	2	544.6	34.9	6848	64.6	51.9	-19.7
	3	544.6	34.9	6848	64.6	54.2	-16.1

APPENDIX G

MASS DISTRIBUTION DATA

G.1 Mass Overlap Distribution Data for Individual Density Treatments

Table G.1. Simulated mass overlap data for 416.5 kg/m^3 density treatment (litter A).

		Controller Settings					
Treatment ID	Rep	Density (kg/m^3)	Gate Height (cm)	Target Rate (kg/ha)	Mean Rate (kg/ha)	Std. Dev. (kg/ha)	CV (%)
	1	416.5	17.8	1743	1694	482	28.4
P	2	416.5	17.8	1743	1419	321	22.6
	3	416.5	17.8	1743	1766	632	35.8
	1	416.5	17.8	3486	2884	772	26.8
Q	2	416.5	17.8	3486	3444	1269	24.6
	3	416.5	17.8	3486	3187	900	28.2
	1	416.5	34.9	3424	3195	736	23.0
R	2	416.5	34.9	3424	2993	690	26.3
	3	416.5	34.9	3424	3323	837	25.2
	1	416.5	34.9	6848	6565	930	18.6
S	2	416.5	34.9	6848	6085	1122	18.4
	3	416.5	34.9	6848	6308	3634	19.6

Table G.2. Simulated mass overlap data for 352.4 kg/m^3 density treatment (litter A).

		Controller Settings					
Treatment ID	Rep	Density (kg/m^3)	Gate Height (cm)	Target Rate (kg/ha)	Mean Rate (kg/ha)	Std. Dev. (kg/ha)	CV (%)
	1	352.4	17.8	1743	1935	413	21.4
P1	2	352.4	17.8	1743	2311	822	35.6
	3	352.4	17.8	1743	1845	882	29.6
	1	352.4	17.8	3486	3836	755	19.7
Q1	2	352.4	17.8	3486	4807	1416	29.5
	3	352.4	17.8	3486	4518	1890	41.8
	1	352.4	34.9	3424	4490	1310	29.2
R1	2	352.4	34.9	3424	3944	894	22.7
	3	352.4	34.9	3424	3858	709	18.4
	1	352.4	34.9	6848	7150	2314	32.4
S1	2	352.4	34.9	6848	8070	1442	17.9
	3	352.4	34.9	6848	8646	2708	31.3

Table G.3. Simulated mass overlap data for 480.5 kg/m^3 density treatment (litter B).

Treatment ID	Rep	Controller Settings: Density (kg/m^3)	Controller Settings: Gate Height (cm)	Controller Settings: Target Rate (kg/ha)	Mean Rate (kg/ha)	Std. Dev. (kg/ha)	CV (%)
E	1	480.6	17.8	1743	1597	417	29.3
	2	480.6	17.8	1743	1697	390	25.7
	3	480.6	17.8	1743	1590	367	25.9
F	1	480.6	17.8	3486	3059	725	26.5
	2	480.6	17.8	3486	3162	678	24.0
	3	480.6	17.8	3486	3349	896	30.0
G	1	480.6	34.9	3424	3023	789	29.2
	2	480.6	34.9	3424	3146	657	27.2
	3	480.6	34.9	3424	3345	768	25.7
H	1	480.6	34.9	6848	6045	1538	28.5
	2	480.6	34.9	6848	6516	1876	32.2
	3	480.6	34.9	6848	6169	1660	30.1

Table G.4. Simulated mass overlap data for 544.6 kg/m^3 density treatment (litter B).

Treatment ID	Rep	Controller Settings: Density (kg/m^3)	Controller Settings: Gate Height (cm)	Controller Settings: Target Rate (kg/ha)	Mean Rate (kg/ha)	Std. Dev. (kg/ha)	CV (%)
E2	1	544.6	17.8	1743	1337	327	27.4
	2	544.6	17.8	1743	1497	334	25.0
	3	544.6	17.8	1743	1365	324	26.6
F2	1	544.6	17.8	3486	3005	788	29.4
	2	544.6	17.8	3486	2660	652	27.5
	3	544.6	17.8	3486	2848	776	30.5
G2	1	544.6	34.9	3424	2584	726	31.4
	2	544.6	34.9	3424	2806	690	27.5
	3	544.6	34.9	3424	2689	579	24.1
H2	1	544.6	34.9	6848	5616	1303	26.0
	2	544.6	34.9	6848	5816	1219	23.5
	3	544.6	34.9	6848	5478	1225	25.0

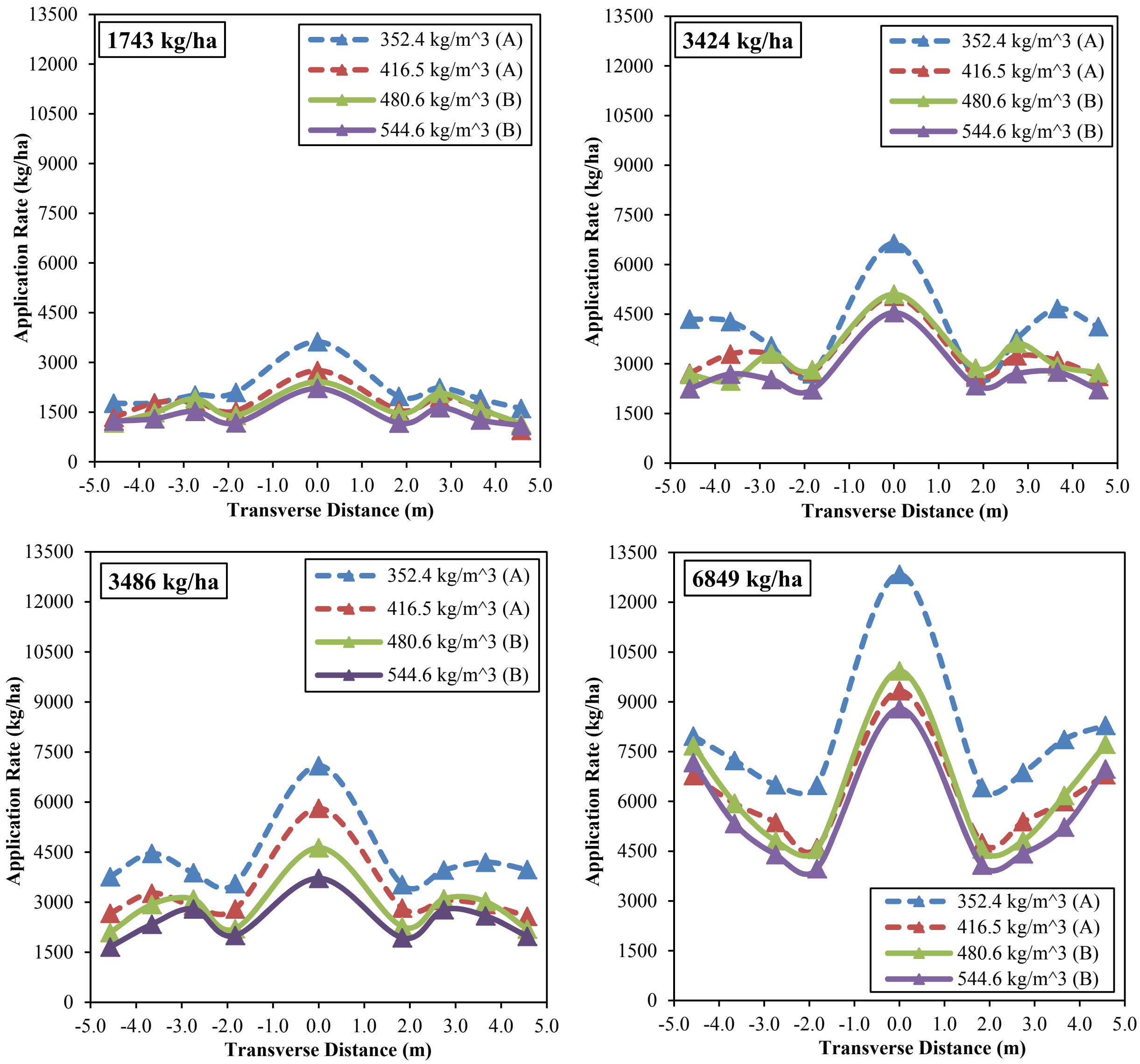

Figure G.1. Mass overlap patterns at different density treatments by litter type (A and B) and application rate.

Table G.5. P-values for comparison between standardized distribution patterns at 352.4 kg/m^3 and 416.5 kg/m^3 density treatments (litter A).

Rate	Transverse Location (m)								
(kg/ha)	-4.6	-3.7	-2.7	-1.8	0.0	1.8	2.7	3.7	4.6
1743	0.6961	0.1069	0.4154	0.1905	0.6152	0.7804	0.2568	0.4872	0.2967
3424	0.4898	0.5831	0.9744	0.8228	0.3259	0.2682	0.8527	0.5444	0.0737
3486	0.1199	0.7515	0.1764	0.0023[a]	0.3235	0.0159[a]	0.2464	0.1013	0.0654
6848	0.2738	0.8249	0.9257	0.3117	0.3901	0.7876	0.8337	0.2758	0.5594

a) Patterns are significantly different at these locations (α=0.05).

Table G.6. P-values for comparison between standardized distribution patterns at 480.6 kg/m^3 and 544.6 kg/m^3 density treatments (litter B).

Rate	Transverse Location (m)								
(kg/ha)	-4.6	-3.7	-2.7	-1.8	0.0	1.8	2.7	3.7	4.6
1743	0.0660	0.1377	0.9057	0.8196	0.4203	0.9828	0.3492	0.4505	0.2159
3424	0.4275	0.0326[a]	0.6650	0.7238	0.2718	0.4691	0.8036	0.7787	0.5360
3486	0.8963	0.0029[a]	0.2409	0.0480[a]	0.2534	0.3760	0.1040	0.5485	0.6638
6848	0.3007	0.1192	0.8001	0.1375	0.0120[a]	0.5682	0.2871	0.0047[a]	0.0571

a) Patterns are significantly different at these locations (α=0.05).

Table G.7. P-values for comparison between Litter A and B standardized distribution patterns.

Rate	Transverse Location (m)								
(kg/ha)	-4.6	-3.7	-2.7	-1.8	0.0	1.8	2.7	3.7	4.6
1743	0.3340	0.1182	0.2598	0.1467	0.6457	0.5452	0.2557	0.6908	0.3623
3424	0.0553	0.1529	0.0716	0.7725	0.1660	0.2575	0.0663	0.3365	0.1048
3486	0.0987	0.0085[a]	0.2479	0.0008[a]	0.4087	0.0652	0.0984	0.0874	0.0997
6848	0.4156	0.7980	0.4413	0.3876	0.2169	0.9212	0.5182	0.0055[a]	0.0063[a]

a) Patterns are significantly different at these locations (α=0.05).

APPENDIX H

LABVIEW PROGRAM

H.1 LabView Program Used For Acquiring Capacitance Sensor Output

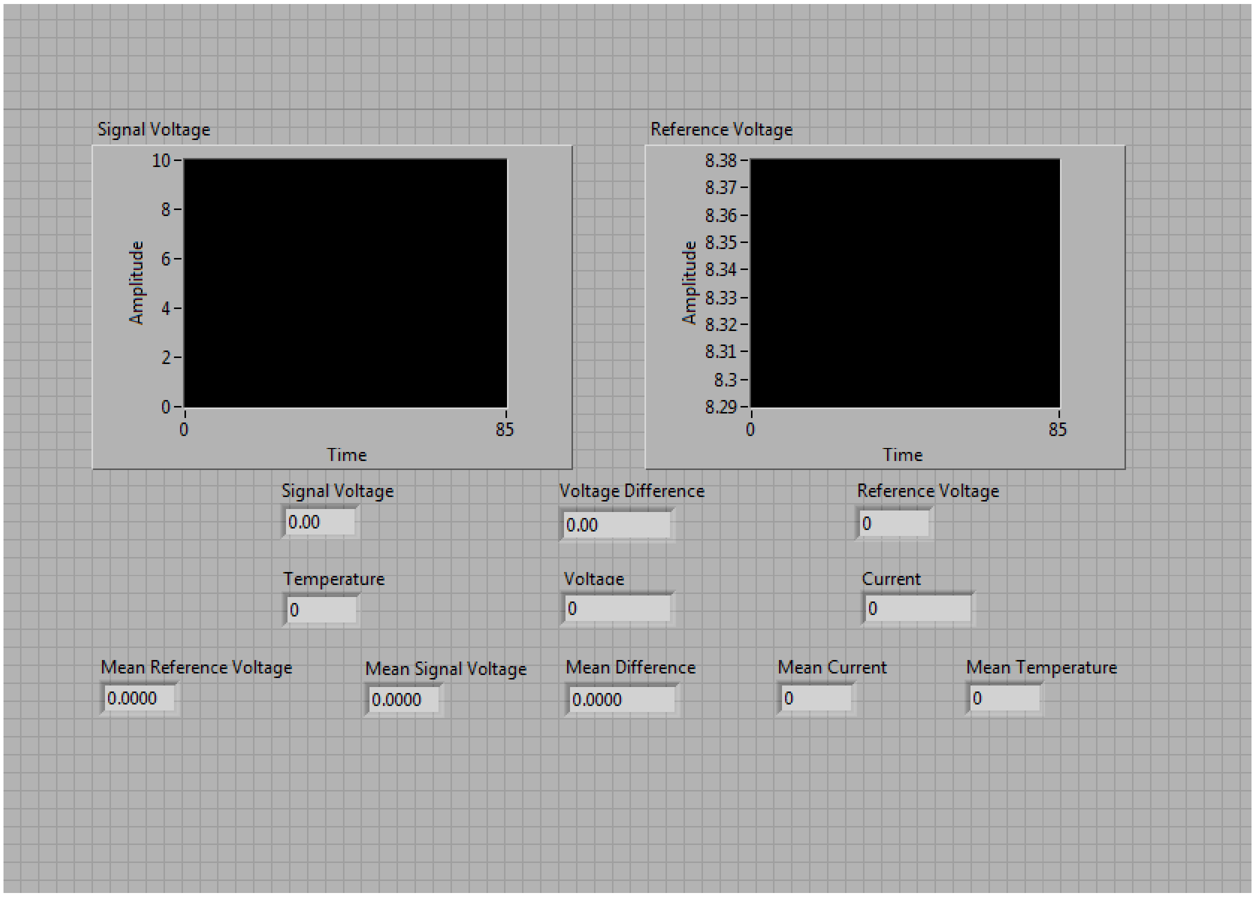

Figure H.1. Front panel view of LabView program used for acquiring capacitance sensor output.

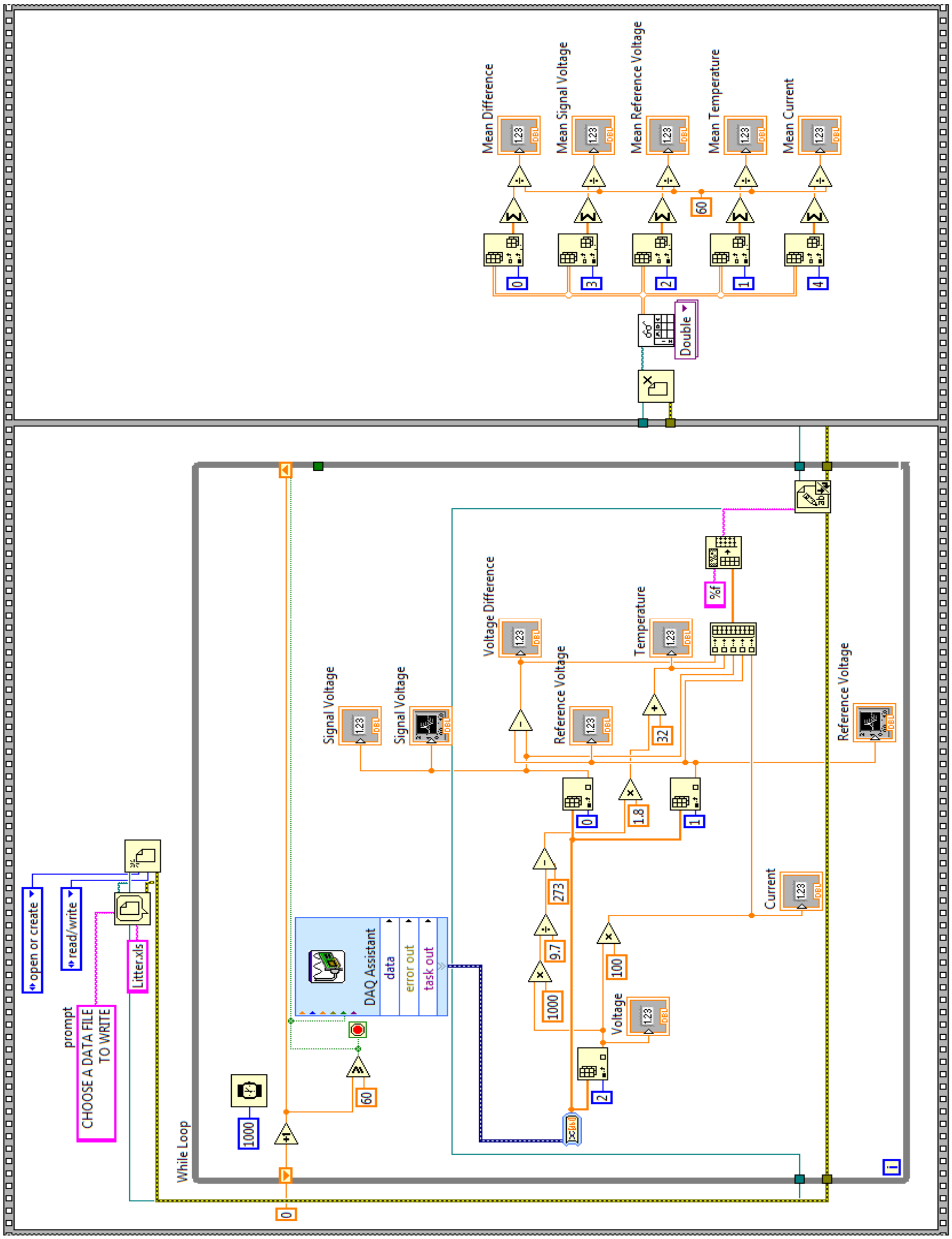

Figure H.2. Block diagram of LabView program for acquiring capacitance sensor output.

APPENDIX I

DIFFERENTIAL VOLTAGE DATA

I.1 Calibration Group: Sensor Output Data for Individual Replications

Table I.1. Replication 1 sensor output data for density treatment A.

Moisture Content (%)	Bulk Density (kg/m^3)	Signal Voltage (V)	Reference Voltage (V)	Differential Voltage (V)	Temperature (^oC)
16.2	412.5	6.51	8.40	1.89	24.4
19.3	444.9	5.30	8.38	3.08	24.3
22.1	430.9	4.08	8.36	4.28	24.1
25.2	434.2	3.31	8.37	5.06	24.1
28.3	432.8	2.19	8.35	6.16	24.1
31.4	422.5	0.93	8.32	7.35	23.9
34.3	425.4	0.57	8.33	7.76	24.2
37.0	411.8	0.41	8.33	7.92	24.1
40.4	403.6	0.28	8.32	8.04	24.0
42.9	391.3	0.15	8.32	8.17	23.9

Table I.2. Replication 2 sensor output data for density treatment A.

Moisture Content (%)	Bulk Density (kg/m^3)	Signal Voltage (V)	Reference Voltage (V)	Differential Voltage (V)	Temperature (^oC)
16.2	414.8	6.56	8.41	1.85	24.3
19.3	427.6	5.25	8.41	3.16	23.9
22.1	424.3	4.36	8.38	4.02	24.3
25.2	429.5	3.13	8.36	5.24	23.9
28.3	429.4	2.31	8.34	6.03	23.9
31.4	415.0	1.00	8.34	7.34	24.0
34.3	415.7	0.55	8.34	7.79	24.3
37.0	395.6	0.48	8.34	7.95	23.9
40.4	399.5	0.29	8.33	8.03	24.3
42.9	386.4	0.17	8.33	8.51	23.9

Table I.3. Replication 3 sensor output data for density treatment A.

Moisture Content (%)	Bulk Density (kg/m^3)	Signal Voltage (V)	Reference Voltage (V)	Differential Voltage (V)	Temperature (^{o}C)
16.2	422.3	6.54	8.42	1.88	24.4
19.3	425.8	5.39	8.41	3.01	24.3
22.1	427.6	4.32	8.38	4.07	24.5
25.2	430.9	3.46	8.37	4.91	24.4
28.3	444.5	1.93	8.34	6.41	24.3
31.4	421.8	1.05	8.34	7.29	24.1
34.3	419.1	0.55	8.34	7.78	24.2
37.0	420.5	0.44	8.33	7.89	24.2
40.4	394.7	0.30	8.33	8.03	24.1
42.9	396.0	0.16	8.33	8.16	24.3

Table I.4. Replication 1 sensor output data for density treatment B.

Moisture Content (%)	Bulk Density (kg/m^3)	Signal Voltage (V)	Reference Voltage (V)	Differential Voltage (V)	Temperature (^{o}C)
16.2	478.8	6.03	8.40	2.37	24.2
19.3	516.5	3.82	8.36	4.54	24.1
22.1	500.3	2.71	8.34	5.63	23.9
25.2	504.1	1.71	8.35	6.64	24.4
28.3	498.5	1.04	8.33	7.29	24.2
31.4	488.4	0.29	8.32	8.03	24.4
34.3	493.8	0.24	8.33	8.09	24.3
37.0	478.1	0.22	8.33	8.11	24.3
40.4	468.6	0.17	8.32	8.15	24.3
42.9	454.3	0.11	8.32	8.21	24.2

Table I.5. Replication 2 sensor output data for density treatment B.

Moisture Content (%)	Bulk Density (kg/m^3)	Signal Voltage (V)	Reference Voltage (V)	Differential Voltage (V)	Temperature (^oC)
16.2	481.6	6.11	8.41	2.29	24.1
19.3	496.4	3.74	8.38	4.64	24.3
22.1	492.6	2.51	8.35	5.84	24.2
25.2	500.3	2.14	8.35	6.21	24.2
28.3	502.5	0.98	8.33	7.36	24.3
31.4	481.8	0.46	8.34	7.88	24.1
34.3	482.6	0.30	8.33	8.04	24.1
37.0	459.3	0.27	8.33	8.06	24.2
40.4	463.8	0.19	8.33	8.14	24.4
42.9	448.6	0.12	8.33	8.21	23.9

Table I.6. Replication 3 sensor output data for density treatment B.

Moisture Content (%)	Bulk Density (kg/m^3)	Signal Voltage (V)	Reference Voltage (V)	Differential Voltage (V)	Temperature (^oC)
16.2	490.2	5.99	8.41	2.42	24.1
19.3	494.3	3.95	8.38	4.43	24.2
22.1	496.4	2.62	8.35	5.73	24.3
25.2	498.6	1.69	8.35	6.66	24.3
28.3	516.0	1.00	8.33	7.33	24.1
31.4	489.7	0.40	8.33	7.94	24.0
34.3	486.5	0.30	8.34	8.03	24.3
37.0	488.1	0.21	8.33	8.12	24.3
40.4	458.2	0.18	8.33	8.15	23.9
42.9	459.8	0.11	8.33	8.22	24.3

Table I.7. Replication 1 sensor output data for density treatment C.

Moisture Content (%)	Bulk Density (kg/m^3)	Signal Voltage (V)	Reference Voltage (V)	Differential Voltage (V)	Temperature (^oC)
16.2	566.8	5.64	8.39	2.75	24.1
19.3	611.4	2.79	8.35	5.56	24.1
22.1	592.1	1.31	8.32	7.01	24.3
25.2	596.6	0.80	8.34	7.54	24.0
28.3	590.1	0.38	8.32	7.95	24.3
31.4	578.6	0.15	8.32	8.17	23.9
34.3	584.5	0.11	8.33	8.22	24.1
37.0	565.9	0.10	8.33	8.23	24.2
40.4	554.6	0.09	8.32	8.24	24.3
42.9	537.7	0.07	8.32	8.26	24.5

Table I.8. Replication 2 sensor output data for density treatment C.

Moisture Content (%)	Bulk Density (kg/m^3)	Signal Voltage (V)	Reference Voltage (V)	Differential Voltage (V)	Temperature (^oC)
16.2	570.1	5.61	8.40	2.79	24.0
19.3	587.6	2.72	8.36	5.64	24.2
22.1	583.0	1.28	8.34	7.05	24.3
25.2	590.2	0.67	8.34	7.67	24.3
28.3	594.8	0.38	8.33	7.95	24.1
31.4	570.3	0.17	8.33	8.17	24.0
34.3	571.3	0.14	8.33	8.22	24.1
37.0	543.7	0.11	8.33	8.22	23.9
40.4	549.0	0.09	8.33	8.24	23.9
42.9	531.0	0.07	8.33	8.25	24.3

Table I.9. Replication 3 sensor output data for density treatment C.

Moisture Content (%)	Bulk Density (kg/m^3)	Signal Voltage (V)	Reference Voltage (V)	Differential Voltage (V)	Temperature (^oC)
16.2	580.3	5.61	8.40	2.79	24.5
19.3	585.1	2.63	8.36	5.73	24.3
22.1	587.6	1.36	8.34	6.98	24.5
25.2	592.2	0.77	8.34	7.56	24.2
28.3	610.8	0.34	8.33	7.99	24.3
31.4	579.7	0.15	8.33	8.18	24.0
34.3	575.9	0.11	8.33	8.22	24.1
37.0	577.8	0.10	8.33	8.23	24.3
40.4	542.3	0.09	8.33	8.24	24.1
42.9	544.2	0.07	8.33	8.26	24.4

I.2 Validation Group: Sensor Output Data for Individual Replications

Table I.10. Sensor output data for density treatment A.

Moisture Content (%)	Bulk Density (kg/m^3)	Signal Voltage (V)	Reference Voltage (V)	Differential Voltage (V)	Temperature (^oC)
17.4	413.4	6.47	8.37	1.90	23.5
19.1	405.5	5.71	8.36	2.65	23.8
20.0	421.9	5.70	8.36	2.66	23.1
21.0	392.4	5.48	8.35	2.87	23.1
21.1	368.7	5.61	8.36	2.74	23.5
22.8	412.3	4.65	8.34	3.69	23.5
23.4	468.8	3.21	8.32	5.11	23.6
24.1	400.5	3.91	8.33	4.42	23.4
24.5	379.6	3.25	8.32	5.07	23.5
24.8	427.2	4.04	8.33	4.31	23.5
27.2	391.3	2.01	8.30	6.29	23.4
27.3	472.8	1.63	8.30	6.67	23.4
27.4	453.5	1.69	8.30	6.61	23.3
28.6	434.1	1.56	8.30	6.74	23.5
28.8	404.8	1.84	8.29	6.46	24.2

Table I.11. Sensor output data for density treatment B.

Moisture Content (%)	Bulk Density (kg/m^3)	Signal Voltage (V)	Reference Voltage (V)	Differential Voltage (V)	Temperature (°C)
17.4	479.9	5.70	8.36	2.66	23.5
19.1	470.7	4.30	8.34	4.04	23.8
20.0	489.8	4.40	8.33	3.93	23.7
21.0	455.6	3.66	8.32	4.66	24.3
21.1	428.0	3.95	8.33	4.38	23.6
22.8	478.7	3.07	8.32	5.25	23.5
23.4	544.3	1.66	8.30	6.64	23.6
24.1	464.9	2.42	8.31	5.89	23.6
24.5	440.6	1.53	8.30	6.76	23.5
24.8	496.0	2.60	8.31	5.71	23.5
27.2	454.3	1.25	8.29	7.05	23.5
27.3	548.9	0.97	8.29	7.32	23.5
27.4	526.5	0.99	8.29	7.30	23.5
28.6	504.0	0.95	8.29	7.34	23.6
28.8	469.9	0.91	8.28	7.37	23.4

Table I.12. Sensor output data for density treatment C.

Moisture Content (%)	Bulk Density (kg/m^3)	Signal Voltage (V)	Reference Voltage (V)	Differential Voltage (V)	Temperature (°C)
17.4	568.1	5.14	8.35	3.21	23.7
19.1	557.2	3.64	8.33	4.68	23.8
20.0	579.7	3.56	8.32	4.76	23.4
21.0	539.3	2.81	8.31	5.50	23.4
21.1	506.7	2.70	8.31	5.61	23.7
22.8	566.6	1.74	8.30	6.56	23.7
23.4	644.2	0.95	8.29	7.34	23.8
24.1	550.3	1.24	8.30	7.05	23.7
24.5	521.6	0.71	8.29	7.58	23.6
24.8	587.1	1.45	8.44	6.99	23.5
27.2	537.8	0.41	8.29	7.88	23.7
27.3	649.7	0.22	8.29	8.07	23.5
27.4	623.2	0.32	8.29	7.97	23.5
28.6	596.5	0.30	8.29	7.99	23.7
28.8	556.3	0.43	8.28	7.85	23.6

Table I.13. Predicted moisture content of the validation litter samples using the regression models.

Actual Moisture Content (%)	Predicted Moisture Content (%)		
	Model 1	Model 2	Model 3
17.4	16.1	16.0	16.6
19.1	18.1	19.3	18.6
20.0	18.2	19.0	18.7
21.0	18.8	20.8	19.7
21.1	18.4	20.1	19.8
22.8	21.1	22.1	21.1
23.4	25.0	25.4	22.2
24.1	23.1	23.6	21.8
24.5	24.9	25.7	22.5
24.8	22.8	23.2	21.7
27.2	28.3	26.4	22.9
27.3	29.3	27.9	23.2
27.4	29.2	27.6	23.0
28.6	29.6	27.3	23.1
28.8	28.8	27.3	22.9

Table I.14. Capacitor sensor repeatability data (Rep 1, 2 & 3 represents the three tests conducted using the same broiler litter sample).

Rep	Moisture Content (%)	Differential Voltage (V)
1	28.4	6.19
2	28.1	6.12
3	28.4	6.08
Mean	28.3	6.13
Std. Dev.	0.12	0.06

APPENDIX J

NIR SPECTRAL DATA

J.1 NIR SPECTRAL DATA FOR CALIBRATION GROUP

Table J.1. Replication 1 NIR absorbance values at selected wavelengths for the calibration group.

Moisture Content	Absorbance Values at different wavelengths (nm)										
(%)	1400	1410	1420	1430	1440	1900	1910	1920	1930	1940	1950
16.2	0.51	0.54	0.56	0.58	0.59	0.76	0.82	0.86	0.88	0.88	0.87
19.3	0.56	0.59	0.62	0.64	0.64	0.83	0.89	0.93	0.95	0.95	0.94
22.1	0.56	0.60	0.63	0.65	0.66	0.87	0.93	0.97	0.99	0.99	0.98
25.2	0.58	0.62	0.65	0.67	0.68	0.90	0.97	1.01	1.03	1.03	1.01
28.3	0.61	0.65	0.69	0.71	0.72	0.94	1.01	1.05	1.07	1.07	1.06
31.4	0.67	0.72	0.75	0.78	0.79	1.02	1.09	1.12	1.14	1.14	1.12
34.3	0.70	0.76	0.80	0.82	0.83	1.09	1.17	1.21	1.22	1.22	1.21
37.0	0.73	0.80	0.84	0.86	0.88	1.15	1.23	1.27	1.28	1.28	1.27
40.4	0.80	0.87	0.91	0.94	0.95	1.23	1.31	1.35	1.36	1.36	1.35
42.9	0.89	0.97	1.02	1.04	1.06	1.35	1.43	1.46	1.48	1.47	1.46

Table J.2. Replication 2 NIR absorbance values at selected wavelengths for the calibration group.

Moisture Content	Absorbance Values at different wavelengths (nm)										
(%)	1400	1410	1420	1430	1440	1900	1910	1920	1930	1940	1950
16.2	0.51	0.54	0.57	0.58	0.59	0.77	0.83	0.87	0.89	0.89	0.88
19.3	0.56	0.59	0.62	0.64	0.64	0.83	0.89	0.93	0.94	0.94	0.93
22.1	0.56	0.60	0.63	0.64	0.65	0.86	0.93	0.97	0.98	0.98	0.97
25.2	0.58	0.62	0.66	0.67	0.68	0.90	0.97	1.01	1.02	1.02	1.01
28.3	0.60	0.65	0.68	0.70	0.71	0.93	1.00	1.04	1.06	1.06	1.05
31.4	0.68	0.74	0.77	0.79	0.81	1.04	1.11	1.15	1.16	1.16	1.15
34.3	0.71	0.76	0.80	0.82	0.83	1.08	1.14	1.18	1.19	1.19	1.18
37.0	0.74	0.80	0.85	0.87	0.88	1.16	1.23	1.27	1.29	1.29	1.27
40.4	0.80	0.87	0.92	0.94	0.95	1.24	1.32	1.35	1.37	1.37	1.35
42.9	0.89	0.96	1.01	1.04	1.05	1.34	1.42	1.46	1.47	1.47	1.45

Table J.3. Replication 3 NIR absorbance values at selected wavelengths for the calibration group.

Moisture Content (%)	Absorbance Values at different wavelengths (nm)										
	1400	1410	1420	1430	1440	1900	1910	1920	1930	1940	1950
16.2	0.52	0.55	0.57	0.58	0.59	0.76	0.82	0.85	0.87	0.87	0.86
19.3	0.56	0.60	0.62	0.64	0.65	0.84	0.90	0.94	0.95	0.95	0.94
22.1	0.56	0.60	0.63	0.65	0.66	0.86	0.93	0.97	0.99	0.99	0.98
25.2	0.57	0.62	0.65	0.67	0.68	0.89	0.96	1.00	1.02	1.02	1.00
28.3	0.61	0.66	0.69	0.71	0.72	0.94	1.02	1.06	1.07	1.07	1.06
31.4	0.68	0.73	0.77	0.79	0.80	1.04	1.11	1.15	1.16	1.16	1.15
34.3	0.70	0.76	0.80	0.82	0.84	1.10	1.17	1.21	1.23	1.23	1.21
37.0	0.73	0.80	0.84	0.86	0.88	1.15	1.23	1.27	1.28	1.28	1.27
40.4	0.81	0.88	0.93	0.95	0.97	1.25	1.33	1.37	1.38	1.38	1.36
42.9	0.90	0.97	1.02	1.05	1.07	1.36	1.43	1.47	1.48	1.48	1.47

J.2 NIR Spectral Data for Validation Group

Table J.4. NIR absorbance values at selected wavelengths for the validation group.

Moisture Content (%)	Absorbance Values at different wavelengths (nm)										
	1400	1410	1420	1430	1440	1900	1910	1920	1930	1940	1950
19.1	0.59	0.63	0.66	0.67	0.69	0.87	0.94	0.97	0.99	0.99	0.98
20.0	0.57	0.61	0.64	0.66	0.67	0.86	0.93	0.97	0.99	0.99	0.98
21.0	0.58	0.62	0.66	0.68	0.69	0.88	0.95	0.99	1.01	1.01	1.00
21.1	0.60	0.64	0.67	0.69	0.70	0.89	0.95	0.99	1.01	1.01	1.00
22.8	0.59	0.63	0.67	0.69	0.70	0.89	0.97	1.01	1.03	1.03	1.02
23.4	0.63	0.68	0.72	0.74	0.75	0.95	1.03	1.07	1.09	1.09	1.08
24.1	0.62	0.66	0.70	0.72	0.73	0.93	1.01	1.05	1.07	1.07	1.05
24.5	0.61	0.65	0.69	0.71	0.72	0.93	1.00	1.05	1.06	1.06	1.05
24.8	0.61	0.66	0.69	0.71	0.72	0.93	1.00	1.05	1.06	1.06	1.05
27.2	0.65	0.70	0.74	0.77	0.78	0.99	1.07	1.11	1.13	1.13	1.11
27.3	0.69	0.74	0.78	0.80	0.81	1.03	1.10	1.14	1.16	1.16	1.14
27.4	0.65	0.70	0.73	0.76	0.77	0.98	1.06	1.10	1.11	1.11	1.10
28.6	0.64	0.69	0.72	0.75	0.76	0.98	1.06	1.11	1.13	1.13	1.11
28.8	0.65	0.70	0.74	0.77	0.78	1.01	1.09	1.13	1.15	1.15	1.13

J.3 NIR SPECTRA: SENSOR REPEATABILITY AND ROTATION VS. POINT MEASUREMENTS

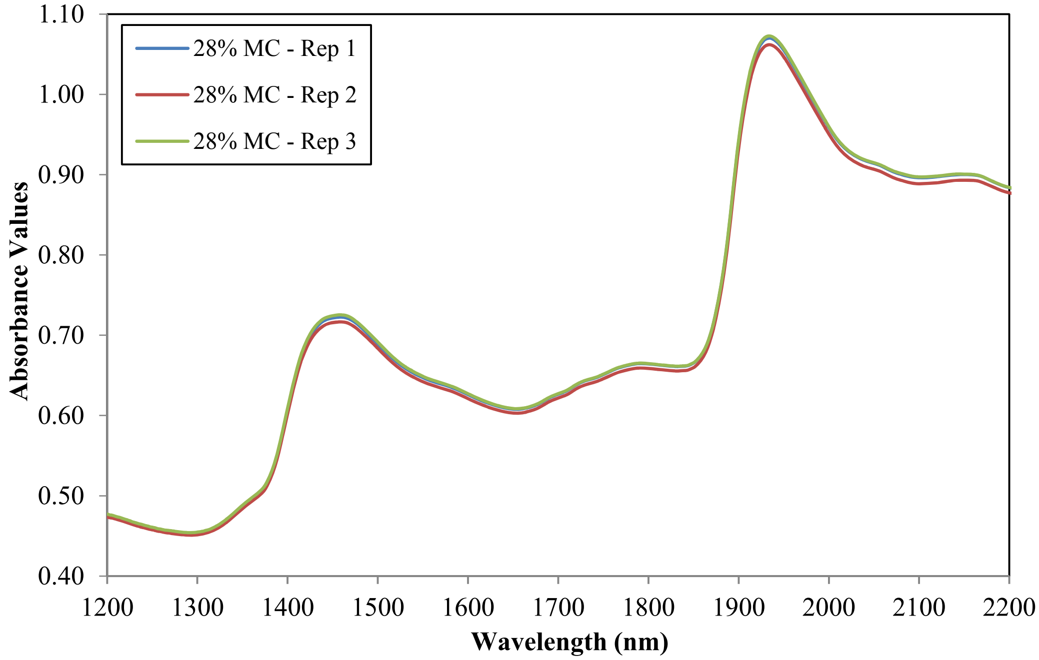

Figure J.1. Plot illustrating repeatability of the NIR spectrometer for broiler litter (Rep 1, 2 & 3 indicates the three tests performed using the same broiler litter sample).

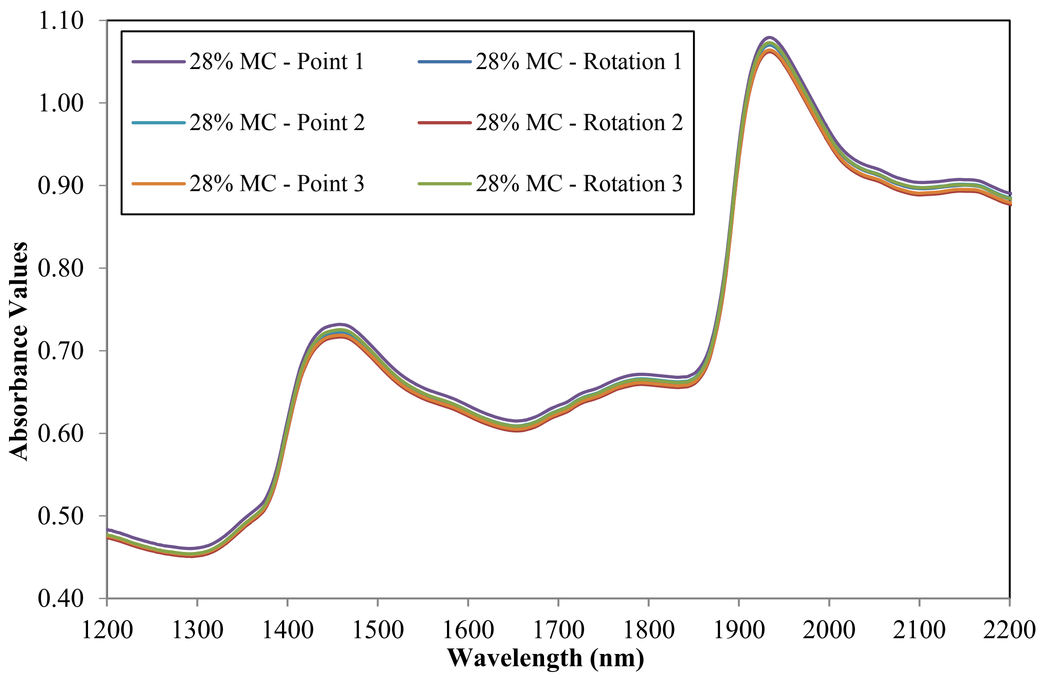

Figure J.2. Comparison of NIR absorption spectra for broiler liter collected using point and rotation measurement features.

J.4 Principal Component Analysis (PCA) for NIR Spectral Data

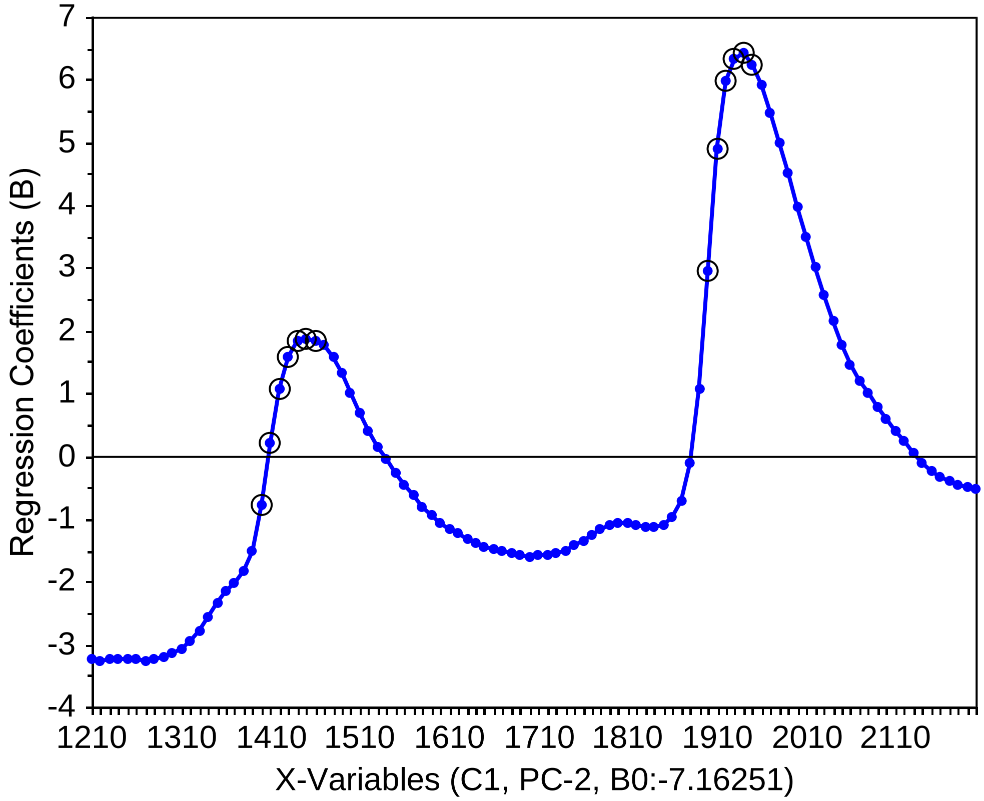

Figure J.3. Regression coefficients obtained from the PCA analysis of spectral data of broiler litter (circles represent important variables highly related to litter moisture content within the spectra).

APPENDIX K

SAS OUTPUT

K.1 SAS Output Data: Variable Selection for Calibration Models

Table K.1. SAS Output for PROC REC (Best 4 variables selection procedure).

Number in Model	Adjusted R-Square	R-Square	Root MSE	SSE	Variables in Model
4	0.997	0.997	0.490	6.006	M1 N1 N4 N5
4	0.997	0.997	0.494	6.099	M1 N2 N4 N5
4	0.997	0.997	0.494	6.104	M3 N2 N4 N5
4	0.997	0.997	0.495	6.137	M4 N2 N4 N5
4	0.997	0.997	0.496	6.146	M2 N1 N4 N5
4	0.997	0.997	0.496	6.152	M2 N2 N4 N5
4	0.997	0.997	0.496	6.158	M3 N1 N4 N5
4	0.997	0.997	0.498	6.199	M5 N2 N4 N5
4	0.997	0.997	0.498	6.207	M4 N1 N4 N5
4	0.997	0.997	0.500	6.239	N1 N4 N5 N6
4	0.997	0.997	0.500	6.257	M5 N1 N4 N5
4	0.997	0.997	0.500	6.260	N2 N4 N5 N6
4	0.997	0.997	0.515	6.638	N3 N4 N5 N6
4	0.997	0.997	0.517	6.689	M1 M2 N4 N5
4	0.997	0.997	0.517	6.690	M4 N3 N4 N5

Table K.2. SAS Output for PROC REC (Best 3 variables selection procedure).

Number in Model	Adjusted R-Square	R-Square	Root MSE	SSE	Variables in Model
3	0.997	0.997	0.511	6.800	N2 N4 N5
3	0.997	0.997	0.513	6.848	N1 N4 N5
3	0.997	0.997	0.514	6.867	N3 N4 N5
3	0.996	0.997	0.522	7.084	M2 N4 N5
3	0.996	0.997	0.522	7.085	M3 N4 N5
3	0.996	0.997	0.522	7.091	M4 N4 N5
3	0.996	0.997	0.522	7.092	M5 N4 N5
3	0.996	0.997	0.523	7.105	M1 N4 N5
3	0.996	0.997	0.525	7.169	N2 N4 N6
3	0.996	0.997	0.526	7.191	N4 N5 N6
3	0.996	0.997	0.531	7.322	N1 N4 N6
3	0.996	0.996	0.558	8.108	M1 N2 N6
3	0.996	0.996	0.559	8.133	N1 N2 N6
3	0.996	0.996	0.564	8.273	N3 N4 N6
3	0.996	0.996	0.565	8.293	M3 N2 N6

Table K.3. SAS Output for PROC REC (Best 2 variables selection procedure).

Number in Model	Adjusted R-Square	R-Square	Root MSE	SSE	Variables in Model
2	0.997	0.997	0.516	7.198	N4 N5
2	0.995	0.995	0.622	10.454	N3 N6
2	0.994	0.994	0.687	12.748	N4 N6
2	0.992	0.992	0.787	16.709	M1 M2
2	0.990	0.990	0.886	21.212	M1 M3
2	0.990	0.990	0.896	21.686	N5 N6
2	0.989	0.989	0.938	23.746	M1 M4
2	0.987	0.988	0.986	26.271	M1 M5
2	0.987	0.988	1.002	27.127	M1 N2
2	0.987	0.988	1.010	27.538	M1 N1
2	0.986	0.987	1.017	27.903	N1 N2
2	0.986	0.987	1.031	28.699	M5 N2
2	0.986	0.987	1.041	29.267	M2 N2
2	0.986	0.987	1.041	29.280	M1 N3
2	0.986	0.987	1.043	29.373	M4 N2

Table K.4. SAS Output for PROC REC (Best 1 variable selection procedure).

Number in Model	Adjusted R-Square	R-Square	Root MSE	SSE	Variables in Model
1	0.974	0.975	1.406	55.332	N4
1	0.974	0.975	1.411	55.738	N3
1	0.973	0.974	1.434	57.611	N5
1	0.973	0.974	1.447	58.631	N2
1	0.972	0.973	1.471	60.602	N6
1	0.968	0.969	1.572	69.164	N1
1	0.951	0.953	1.936	104.991	M5
1	0.951	0.952	1.942	105.602	M4
1	0.949	0.950	1.978	109.509	M3
1	0.944	0.946	2.064	119.326	M2
1	0.933	0.936	2.252	141.988	M1

K.2 ANOVA Results: Comparison Between Actual and Predicted Moisture Values

Table K.5. ANOVA summary statistics for comparison of actual and predicted moisture values obtained from regression model for capacitance sensor (Model 1).

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	305.805	305.805	205.43	<.0001
Error	13	19.351	1.488		
Corrected Total	14	325.157			

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-7.60511	2.18925	-3.47	0.0041
slope	1	1.30287	0.09090	14.33	<.0001

Table K.6. ANOVA summary statistics for comparison of actual and predicted moisture values obtained from regression model for capacitance sensor (Model 2).

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	181.40216	181.40216	151.99	<.0001
Error	13	15.51518	1.19348		
Corrected Total	14	196.91733			

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-0.46913	1.96026	-0.24	0.8146
slope	1	1.00346	0.08139	12.33	0.2436

Table K.7. ANOVA summary statistics for comparison of actual and predicted moisture values obtained from regression model for capacitance sensor (Model 3).

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	52.56929	52.56929	118.89	<.0001
Error	13	5.74804	0.44216		
Corrected Total	14	58.31733			

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	8.31219	1.19315	6.97	<.0001
slope	1	0.54019	0.04954	10.90	<.0001

Table K.8. ANOVA summary statistics for comparison of actual and predicted moisture values obtained from regression model for NIR technique (Predictors: 1400 1930 1940 1950).

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	165.35058	165.35058	143.32	<.0001
Error	13	14.99875	1.15375		
Corrected Total	14	180.34933			

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	2.24015	1.92736	1.16	<.0001
slope	1	0.95804	0.08003	11.97	0.2660

Table K.9. ANOVA summary statistics for comparison of actual and predicted moisture values obtained from regression model for NIR technique (Predictors: 1400 1930 1940).

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	167.79938	167.79938	86.53	<.0001
Error	13	25.20995	1.93923		
Corrected Total	14	193.00933			

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	3.50503	2.49874	1.40	<.0001
slope	1	0.96510	0.10375	9.30	0.1841

Table K.10. ANOVA summary statistics for comparison of actual and predicted moisture values obtained from regression model for NIR technique (Predictors: 1400 1900).

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	180.206	180.206	240.29	<.0001
Error	13	9.749	0.749		
Corrected Total	14	189.956			

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	1.00314	1.55390	0.65	0.0198
slope	1	1.00015	0.06452	15.50	0.5487

Table K.11. ANOVA summary statistics for comparison of actual and predicted moisture values obtained from regression model for NIR technique (Predictors: 1930).

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	121.62913	121.62913	171.86	<.0001
Error	13	9.20020	0.70771		
Corrected Total	14	130.82933			
Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	6.52352	1.50950	4.32	0.0008
slope	1	0.82167	0.06268	13.11	<.0001