ENHANCING PEANUT HARVESTING: EVALUATING FACTORS THAT INFLUENCE RECOVERED YIELD AND DEVELOPING A WEB-BASED FIELD DRYING FORECAST TOOL

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Charles Dillan Burkett
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Accepted by:
Aaron P. Turner, Committee Chair
Kendall R. Kirk, Committee Member
Hunter F. Massey, Committee Member
ABSTRACT

Peanuts have one of the largest economic impacts of agronomic crops in the State of South Carolina. Peanut harvest operations involve several steps (digging, curing, combining) using equipment unique to peanut production, including peanut digger/shaker/inverters. This thesis evaluates several aspects of peanut harvest operations, including how precision agriculture technologies can enhance decision-making and enhance production. Several studies were conducted to analyze how various aspects of peanut harvesting operations contribute to decrease losses in yield and revenue. The first study evaluated the influence of operator experience on mean absolute guidance line deviation during peanut digging operations and the associated effects on recovered yield. This study was completed in two experiments where, in the first experiment, mean absolute guidance line deviation while digging peanuts was measured for operators with varying levels of operation experience. A second experiment was conducted to evaluate how well the perceived row center aligned with the actual row center, as a function of row orientation and seeking distance. Results from the first experiment showed operators with lower experience had significantly higher mean absolute guidance line deviations, relative to automatic steering and high experience operators (3.3 cm (1.3 in), 5.1 cm (2.0 in), 7.6 cm (3.0 in), for automatic steering, high experience, and low experience respectively). This deviation did not translate to significant differences in yield loss between groups, but yield loss was significantly correlated with guidance line deviation. One interpretation of this is that an inexperienced operator paired with an automatic guidance system can perform at the same level or better compared to a
highly skilled operator using manual steering. Results from the second experiment showed no significant effects on cross-track distance from row orientation. However, seeking distance had a significant effect on the cross-track distance where the perceived row center was closer to the actual row center at the far distance. An economic evaluation was conducted based on a $25,000 automatic steering system cost, yield loss projections from this study and others, along with labor costs differences from replacing a high skilled operator with a low skilled operator. It was found that a system would payoff after digging between 96 to 128 ha of peanuts. Another objective of these studies was to analyze the effect of canopy compaction due to wheel traffic on recovered yield and moisture content in peanut digging operations. Peanut digger manufacturers recommend that dual rear wheels be removed when digging peanuts with 2 and 4 row diggers. The removal of dual wheels can be tedious and at times dangerous due to heavy weights and their large size. This removal is recommended as the dual wheels will compact two rows of plants and is thought to affect yield and quality. This study also explored the use of UAS DEMs and orthographic imagery to measure windrow volumes. This was conducted in two separate tests, one in a heavy soil texture and another in a light soil texture. Results showed that in light soil texture canopy traffic compaction had a significant effect on windrow volume and the moisture content at combining, where compacted plots had lower windrow volumes and lower kernel moisture contents at harvest. However, in heavy soil texture plots these effects were found not significant, but similar trends were shown. For both soil textures, canopy traffic compaction did not have a significant effect on recovered yield, however a negative trend in yield was seen in plots that were compacted. A final component of this work was
to create a web-based application to allow farmers to estimate and forecast windrowed peanut drying and to support scheduling of peanut digging and harvesting operations. The application was based on a previously developed windrow drying model, combined with site specific weather forecasts. The application also warns the user of any potential cold weather injury due to near freezing temperatures associated with high peanut moisture contents in the field. The culmination of the results and guidance from these studies can help producers improve peanut harvest decision making to reduce losses and improve profitability.
DEDICATION

I would like to dedicate this thesis to several individuals. First my parents Kim and Chuck Burkett, grandparents, aunts and uncles, and my girlfriend Mackenzie Evans. Without the love and support from each of you this endeavor would not have been possible. Each of you have helped mold me into the person I am today. I appreciate everything each of you have done more than words could express.
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CHAPTER 1. INTRODUCTION

1.1 Overview of Peanut Harvesting and Production operations

Peanuts have one of the largest economic impacts in field crops in the State of South Carolina. Between the years 2012 and 2022 an average of over 35,000 ha (88,000 ac) of peanuts were harvested in the per year, yielding an average of 4,187 kg ha\(^{-1}\) (3,735 lb ac\(^{-1}\)) (USDA, 2019). Using a 10-year average price per pound of $0.49 kg\(^{-1}\) ($0.22 lb\(^{-1}\)) (USDA, 2022a), this resulted in a farm gate revenue of over $72,000,000. Peanuts are also an agronomically unique crop, where the target product is grown 2-3 inches below the ground, much like potatoes. This growing behavior requires specialized machinery and operations that are not used in any other field crop. Machinery specialized for peanut production and harvesting includes peanut digger/shaker/inverters and peanut combine, which can be pull-type or self-propelled. Along with this specialized equipment, the process for harvesting the crop is also unique, consisting of three operations, digging and inversion, curing, and combining.

The digging and inversion process refers to the unearthing and inversion of the plants to expose the target product, the peanut pods, to ambient air and solar radiation to dry them. During this digging process, it is critical that the equipment operator maintain a straight and constant course along the center of the rows they are harvesting. If they do not maintain this course yield losses will occur, preliminary work that motivated this study quantified this loss at 72.64 kg ha\(^{-1}\) cm\(^{-1}\) 165 lb ac\(^{-1}\) in\(^{-1}\) (Samenko, 2020). Several studies have been conducted to find the effects that off-tracking has on lost yield, but none have
been conducted to find the effect that the experience of the operator has on this off-tracking. It would be economically advantageous if a producer was able to hire a lower-cost lower-skill level operator paired with automatic guidance systems to perform normally high skill-requirement operations, such as peanut digging and inversion, at the same level or better compared to highly skilled operators.

Another issue investigated involving peanut digging operations in these collective works includes the effect that canopy and soil compaction due to wheel-traffic has on recovered yield. At least one manufacturers recommends the removal or spacing of dual rear wheels when digging peanuts with a peanut digger, as the dual wheels will drive over and impact two rows of peanuts (KMC, 2015). The removal of dual wheels can be an time consuming task during an already busy time of the year for the producer and can also be dangerous as these tires are large, heavy, and sometimes filled with ballasting fluids. The compaction of the plant canopy can have several effects on the product pertaining to its quality including soil compaction, which may affect digger-caused pod losses, inversion quality and windrow shape, which both may affect the speed at which the product dries down in the field.

The curing process of peanut harvesting operations can be problematic, risky, and stressful on the side of the producer. At times, the producer must balance the risk of cold weather injury during late season harvesting, time and schedule combining for given peanuts that are to be dug and those that are already dug in the field and ensure the product in the field is at a moisture content that is conducive for combining operations. Even in the absence of cold weather events, leaving peanuts to dry in the field for too short of a period
can result in increased drying costs (Butts, 1995) and leaving them for too long can result in quality reduction through increased loose shelled kernels (LSKs) (Ogejo, 2009), increased sound splits and increased yield loss due to wildlife damage (Butts, 1995). Decision support tools are available for other crops and operations concerning the timing of harvesting operations, but none exist for peanut harvesting operations. In this work, a windrowed peanut drying forecaster was developed to assist the producer in timing and scheduling peanut harvesting operations. This application also includes features to warn the user of any potential for impending cold weather injury, and the producer can make a decision to pause digging operations, or prematurely combine the dug peanuts prevent any damages.

1.2 Organization of thesis

Chapter 1 introduces the thesis, including background information on peanut production in the State of South Carolina. This chapter also give information on the objectives of the studies in this work. Chapter 2 presents an investigation into the the influence of operator experience on mean absolute guidance line deviation and associated peanut harvest losses during digging. Chapter 3 investigates the impact of tractor wheel traffic compaction during peanut digging operations on recovered yield and evaluates the potential of UAS orthographic imagery for analyzing windrowed peanut volumes. Chapter 4 presents the initial development of a windrowed peanut drying forecasting web application for Extension and outreach use. Chapter 5 provides conclusions and
suggestions for future work in all these topics. Chapter 6 contains references for all the previous chapters.
CHAPTER 2. INFLUENCE OF OPERATOR EXPERIENCE AND GUIDANCE LINE DEVIATION ON PEANUT DIGGING OPERATIONS

2.1 Introduction

Peanuts (*Arachis hypogaea* L.) are a crop that has a large impact on South Carolina’s agricultural economy. Between the years 2012 and 2022 an average of 35,000 ha (88,000 ac) was in peanut production and resulted in an average yield of 4,187 kg ha\(^{-1}\) (3,735 lb ac\(^{-1}\)) (USDA, 2022b). They are, agronomically a unique row crop requiring specialized equipment for harvesting, including diggers and combines. Because of this additional investment into machinery, among other reasons, producers must maximize crop yield to make the operation as profitable as possible. In peanut digging operations, centerline deviation significantly contributes to yield losses (Ortiz et al., 2013; Roberson and Jordan, 2014; Santos et al., 2019; Vellidis et al., 2013). These studies show that to maximize yield, the tractor's center must follow the exact centerline between the harvested rows during peanut digging operations. Samenko (2020) found that operators tended to deviate south during harvest operations conducted in the northern hemisphere, suggesting that the plants leaned towards the equator. This suggests a hypothesis that peanuts can produce a false row centerline caused by plants leaning to the equator when planted in an east-west orientation, and in turn cause operators to deviate from the actual row centerline.

The lean of peanut plants to the southern direction in the northern hemisphere can be attributed to the phototropic and geotropic growing patterns of the plants. Where the azimuthal direction of prime solar intensity can affect the direction at which a majority of
the plant’s biomass can grow (Ehleringer and Forseth, 1980). Rosa and Forseth (1996) found that gusts of wind can influence the solar intensity that can be absorbed by the plant canopy and can affect the growing behavior. This response to environmental stimuli can cause the canopy of the peanut plant to lean in a certain direction and cause the appearance of a false row centerline. This false row centerline can then cause deviation by the operator digging peanuts and cause a reduction in recovered yield.

General benefits of automated guidance technology include decreased fuel usage, decreases in wasted application of fertilizers and chemicals, and increases in effective field capacity. Using automated steering systems, a producer can be more productive in their fieldwork, covering more acreage in less time. These benefits are not strictly related to peanut production; these benefits can be found in the production of any row crop. Scarfone et al. (2021) studied the increases in productivity and the economic benefits of adopting automatic guidance technology in wheat production. They found that about 0.1 ha (0.25 ac) of land was missed when using manual guidance out of 2.2 ha (5.4 ac) compared to automatic guidance. It was found that there was no statistical significance in the change in effective field capacity. However, the change in field efficiency was found to be significant. Where field efficiency is the ratio between the actual working time of the specific machine in the field against the theoretical maximum working time (ASABE, 2017).

General economic benefits of adopting precision agriculture technologies include the employment of lower-skilled and inexpensive labor to conduct arduous and higher-skilled-level agricultural machinery operations. With the use of technologies such as
automated steering systems, variable rate application, and harvest monitoring systems, a farm owner can delegate some operations to farm laborers and use the saved time to better manage their operations (Barnes et al., 2019; Lowenberg-DeBoer, 2015).

Another aspect of precision agriculture that can motivate a producer to adopt new technologies is labor savings. McFadden et al. (2023), compiled surveys from between 1996 and 2019 to gauge the adoption of precision technologies. The crops analyzed in this survey include corn, soybeans, winter wheat, cotton, rice, and sorghum. They found that adopters of precision technologies such as yield mapping and soil mapping and automated steering systems had 35% less labor hours per bushel of corn produced. They also stated that the actual relationship between the adoption of precision agriculture technologies and labor hours is unclear but would expect an inverse relationship where adopters of these technologies would have less working hours. Using these systems allows the producer to delegate tasks to lower skilled hired labor or to perform these operations themselves with lower fatigue. In a survey by the USDA, in 2022-2023 only 14% of agricultural production operators in the state have adopted the use of precision agriculture technologies (USDA, 2023b).

Many peanut producers in the state of South Carolina are hesitant to adopt precision agriculture technologies such as RTK correct automatic guidance due to the sheer cost of these systems. Whether or not they are currently operating guidance-ready equipment, an initial investment in these types of systems can be upwards of $30,000. Saavoss (2018) studied the profitability of these systems on operations that are producing peanuts. They found benefits of using these technologies for the producer and the public. They stated that
the use of automatic steering systems were associated with a 9% increase in yield and a
15% reduction in fuel and fertilizer expenditures (Saavoss, 2018).

Technologies such as Real Time Kinematic Global Positioning Systems (RTK GPS) allow for high spatial accuracy automatic guidance systems for agricultural equipment. These systems achieve spatial errors less than or equal to 2.5 cm (1.0 in) (Adams, 2019; Griffin et al., 2005; Roberson and Jordan, 2014). Using RTK correction when using automatic steering is critical, as spatial errors with standalone GPS receivers can exceed 10 m (Seyyedhasani et al., 2016).

Applied explicitly to peanut production, the cost savings and revenue from recovered yield by using RTK corrected automatic guidance systems is substantial. Ortiz et al. (2013) found significant differences in net returns due to variables including tillage style, row configuration (planting on twin rows or single rows), row deviation, and the interaction of all three variables. Changes in net returns using RTK-corrected automatic guidance were seen between $323-695 ha⁻¹ ($131-281 ac⁻¹), with constant row deviations greater than 90 mm (3.5 in). Roberson and Jordan (2014) also studied the use of RTK corrections for automatic guidance systems in peanut digging operations. To eliminate the need for a localized base station, this study used a cellular modem on their automatic guidance controller and received cloud-based corrections from the North Carolina Geodetic Survey Real Time Network (NCRTN). They found a 508 kg-ha⁻¹ (453 lb-ac⁻¹) increase in yield when digging with automatic guidance compared to manual steering. This yield recovered when steering manually was found to be significantly different from
automatic steering. However, these results did not evaluate differences between operators, at the same operator drove the tractor for all manual guidance replications.

Using automatic guidance systems helps alleviate the need for high-skilled and experienced operators in unique cropping operations such as peanut digging and harvesting. During peanut digging and harvesting operations, the tractor’s operator must monitor several varied factors unique to peanut operations, including ground speed, conveyor speed, digger depth, and row center alignment. Inexperienced operators in peanut harvesting operations can contribute to yield losses as they are not experienced in monitoring all of these factors to minimize yield losses. Older and more experienced operators can experience some physical stresses and discomfort in manually guiding the tractor during these operations. Karimi et al. (2012) found that operators spent less time in awkward or uncomfortable positions while using automatic guidance when compared to manually steering the machine.

In these experiments a peanut digger equipped with automated depth control was used to eliminate digger depth as a source of yield losses. This technology was developed and tested at Clemson University and digging angle and uses a hydraulic top-link to correct the depth of the implement’s blades. When operating a peanut digger in varying soil texture, the operator must adjust the digger depth to reduce in field losses. (Kirk et al., 2016; Warner, 2015) designed and retrofitted an automatic depth control system to an existing peanut digger. This technology was used in our study to reduce yield variability as a function of digger depth, since it was not a factor tested in this study.
Vellidis et al. (2013) found differences in recovered yield while using automatic guidance for digging peanuts of 745 kg-ha\(^{-1}\) when compared to manually steering during these operations. These differences in yield were found on varying levels of curvature in the working field. For these experiments, crops were planted along varying levels of curvature utilizing Trimble Autopilot\textsuperscript{TM} (Trimble Navigation Limited, Sunnyvale, Cal.), and rows were randomly assigned to be harvested using either the Autopilot or manual guidance. During their 2011 experiments in high curvature scenarios, they saw a 642 kg-ha\(^{-1}\) increase in yields using Autopilot compared to manual guidance.

The blade of the peanut digger/inverter serves two main functions, the first to shear the taproot of the peanut plant and the second to loosen the soil surrounding the area that contains the peanut pods (Samenko, 2021; Warner, 2015). The coulter wheels placed outside and between the two rows cuts the overlapping root and pod structure of the two rows being harvested so they do not tangle and improve their inversion during the lifting and inversion process (Duke, 1968). Deviation from the center of the two rows being harvested compromises several mechanical tasks the peanut digger/inverter implement is performing. Deviation from the row centerline causes the digger blade to loosen soil focus operations around parts of the plant where pods are at their lowest densities, and if far enough off the blade may miss the taproot entirely and not be sheared. The coulters of the digger also perform poorly when deviating, as they will be used to cut parts of the plant with high pod and stem density. The performance decreases in these two mechanisms due to row center deviation can lead to decreases in recovered yield, with losses above and below ground.
Precision agriculture technologies have the potential to improve the efficiency of operations, assist the producer in decision making, and ease the stress of laborious and high-expertise tasks such as peanut digging operations. Several studies have been conducted to find the effects of centerline deviation on peanut harvesting losses, but none have been conducted to find the influence that the experience of the operator has on centerline deviation and yield losses, or variability in yield across several operators steering manually.

2.2 Objectives

The overall goal of this study was to evaluate the steering abilities and mean absolute guidance line deviations of experienced peanut digging and harvesting operators, inexperienced operators, and an automatic steering system. The study evaluated recovered yield and mean absolute guidance line deviation of these groups and evaluated the economics of replacing an experienced operator with an inexperienced operator equipped with an automated steering system, and the benefits to the producer of doing so. To accomplish these objectives two experiments were conducted to evaluate different factors in peanut digging and harvesting operations that can contribute to mean absolute guidance line deviation. The first experiment analyzed an operator’s ability to distinguish actual from apparent row center in undug peanuts, and what effect planted row orientation and seeking distance has on an operator’s perceived row center. The second experiment evaluates the operator’s ability to maintain a consistent course and minimize guidance line deviations during peanut digging operations. Operators were surveyed to gauge their operation
experience and placed into high and low experience groups based on their survey responses. For comparison between manual steering, RTK-corrected automatic steering replications were included.

2.3 Materials and Methods

2.3.1 Field Location

Both experiments were conducted at Clemson University’s Edisto Research and Education Center (EREC) in Blackville, SC (33.37 N, -81.33 W). Perceived row center tests (Experiment 1) were conducted in October 2022 using two plots of mature Virginia type (Emery variety) peanuts with rows oriented, East-to-West and North-to-South. Guidance line deviation experiments (Experiment 2) were conducted over two years. In the 2019 tests, harvest was conducted in November for a runner variety (FloRun 331). In 2022, harvest was conducted in October using a Virginia type Emery variety of peanuts. For both years, plots consisted of two single rows planted on 96.5 cm (38 in) row centers. Plots were cut to lengths of 15.2 m (50 ft) and a randomized block design was chosen for operator assignments for each plot. Where each operator had four assigned plots for harvest in 2019 tests and six plots assigned for harvest in 2022 tests.

2.3.2 Guidance Line Deviation and Cross-Track Distance Calculations

Both experiments rely on accurate measurement of the perpendicular distance between a point along an A-B line and the center of the A-B line, known as the cross-track distance. This cross-track distance was used to find the perpendicular distance between the
apparent and actual row center in Experiment 1, and the distance between the center of the tractor and the actual row center for Experiment 2. For this, the Haversine cross-track distances found using methods from Samenko (2020) and Veness (2022). As this method finds the great circle perpendicular distance along an A-B line. Where the distance from points A to C is found Equation (1), and to find the perpendicular cross-track between points along the A-B line the bearing between points A and B and points A and C are found Equation (2).

Equation (3) calculates the perpendicular distance between points A and C. This was used for analysis in both experiments where in experiment 1 this was used to find the distance between the operator’s perceived row center and the actual row center. In experiment 2, this method was used to find the perpendicular distance between the center of the tractor and the A-B guidance line.

\[
d_{AC} = R \times c \\
c = 2 \times \text{atan2}(\sqrt{a}, \sqrt{1-a}) \\
a = \sin^2\left(\frac{(\phi_c - \phi_A)}{2}\right) + \cos\phi_A \times \cos\phi_c \\
\quad \times \sin^2\left(\frac{\lambda_C - \lambda_A}{2}\right)
\]

Where,
\[
d_{AC} = \text{Distance from point A to point C (km)}, \\
R = \text{Radius of the Earth (6378.137 km)}, \\
\phi_c = \text{Latitude for point C (radians)},
\]
\( \phi_A \) = Latitude for point A (radians),

\( \lambda_C \) = Longitude for point C (radians),

\( \lambda_A \) = Longitude for point A (radians).

\[
\theta_{12} = \text{atan2}(\sin(\lambda_2 - \lambda_1) \ast \cos(\phi_2), \cos(\phi_1)) \times \sin(\phi_2) - \sin(\phi_1) \ast \cos(\phi_2) \times \cos(\lambda_2 - \lambda_1)) \tag{2}
\]

Where,

\( \theta_{12} \) = Bearing (radians),

\( \lambda_2 \) = Longitude for point 2 (radians),

\( \lambda_1 \) = Longitude for point 1 (radians),

\( \phi_2 \) = Latitude for point 2 (radians),

\( \phi_1 \) = Latitude for point 1 (radians).

\[
D_{XT} = \text{asin}\left(\sin\left(\frac{d_{AC}}{R}\right) \ast \sin(\theta_{AC} - \theta_{AB})\right) \times R \tag{3}
\]

Where,

\( D_{XT} \) = Perpendicular cross-track distance from point C to the A-B line (km),

\( \theta_{AC} \) = Bearing from point A to point C (radians),

\( \theta_{AB} \) = Bearing from point A to point B (radians).
Results of calculations from Equation (3) will output values between $-\infty$ and $+\infty$. These results are relative to the side of the A-B line the point is on, where those to the left of the A-B line are less than zero and those to the right of the A-B line are greater than zero.

For experiments testing an operator’s ability to distinguish the actual row center, on plots that were planted in a roughly North-to-South row orientation, operators faced North for the experiment and negative values correlate to a point west of the row centerline and positive values correlate to a point east of the row centerline. This principle is the same for rows planted in an East-to-West row orientation where operators faced West when taking points. In this scenario, negative distances indicate a point to the South of the row centerline and positive numbers indicate a point North of the row centerline. Figure 1 and Figure 2 visualize these for each row orientation.

![Diagram](image)

**Figure 1. Visualization of distance and direction for North-to-South oriented plots**
2.3.3  Experiment 1: Perceived Row Center

This experiment was conducted to find the influences of row orientation and seeking distance on an operator’s ability to distinguish the actual row-center of a row of peanuts. Operators (N = 7) guided a test administrator who positioned a Emlid Reach RS+ RTK GPS receiver (Emlid Inc., Budapest, Hungary) on a survey pole to the operator’s perceived row-center at two different distances, 15.2 and 32.3 m (50 and 106 ft). These tests were conducted in plots planted in a North-to-South (Figure 3) and an East-to-West (Figure 4) orientation. RTK corrections were received from a base station placed in the field and all points were taken with an RTK fix. Each operator conducted six positioning instances for each orientation and distance combination (N=24 per operator). Operators faced North for plots planted North-to-South and West for plots planted East-to-West.
Figure 3. North-South plots

Figure 4. East-West plots
2.3.4 Experiment 2: Impact of Operator Experience on Guidance Line Deviation

Participant Requirement and Experience Survey

For this experiment, gauging the level of operator experience was critical for data analysis. A survey instrument was developed to gauge the general agricultural and peanut harvesting equipment operation experience of all participants. These surveys were given digitally using Qualtrics XM (Qualtrics, LLC., Provo, Utah) and were given to the groups before the experiments began. Experience levels in peanut harvesting operations were defined in two categories, high and low. Where high experienced individuals were defined as those who work fulltime as farmers and produce peanuts. High experienced operators were also defined to include those who conduct peanut research and regularly operate these types of equipment. Low levels of operator experience were defined to include those individuals who were hobby operators, those who have operated agricultural equipment and have never harvested peanuts, and those that have never operated any type of agricultural equipment. Table 1 visualizes the matrix of possible answers and where the participant would rank based on their response. If an individual responded as a professional row crop producer, hobby peanut farmer or professional peanut farmer they would be in the high experience category. All other responses would qualify the participant for the low experience category. For instances where an operator would respond in a category that would qualify them as low experience, and answered in a category that would qualify them as high experience, that operator would be classified as high experience. For example, if an operator responded that they perform general agriculture operations on occasion, row
crop operations semi-regularly, and peanut digging and harvesting operations professionally, they would be classified as high experience. Operators who had previously performed peanut digging operations were asked how they thought their performance would compare to autosteer and their peers, they were given the choices “Better” or “Worse.” Table 2 displays the results from this survey, where the value for each experience category and experience level option represents the count each combination was chosen.

Table 1: Survey Interpretation

<table>
<thead>
<tr>
<th>Operation Category</th>
<th>No previous experience</th>
<th>I've conducted these operations on a few occasions, but not regularly</th>
<th>I conduct these operations semi regularly or as a hobby</th>
<th>I conduct these operations professionally</th>
</tr>
</thead>
<tbody>
<tr>
<td>General Ag Operations (loader, mowing, etc.)</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
</tr>
<tr>
<td>Row Crop Operations (planting, harvesting, chemical application)</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td>Peanut Digging and Harvesting</td>
<td>Low</td>
<td>Low</td>
<td>High</td>
<td>High</td>
</tr>
</tbody>
</table>

Table 2: Survey Results

<table>
<thead>
<tr>
<th>Operation Category</th>
<th>No previous experience</th>
<th>I've conducted these operations on a few occasions, but not regularly</th>
<th>I conduct these operations semi regularly or as a hobby</th>
<th>I conduct these operations professionally</th>
</tr>
</thead>
<tbody>
<tr>
<td>General Ag Operations (loader, mowing, etc.)</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>9</td>
</tr>
<tr>
<td>Row Crop Operations (planting, harvesting, chemical application)</td>
<td>1</td>
<td>6</td>
<td>1</td>
<td>7</td>
</tr>
<tr>
<td>Peanut Digging and Harvesting</td>
<td>5</td>
<td>3</td>
<td>2</td>
<td>5</td>
</tr>
</tbody>
</table>
This study uses data from testing in both 2019 and 2022, participants from both years were given the same survey and the population for high, low, and automatic steering are shown in Table 3. There were two operators who participated in both 2019 and 2022 testing; one operator was classified in the high experience category and the other in the low experience category. For the seven operators who responded that they were professional row crop operators, also fit into both high experience peanut digging categories.

<table>
<thead>
<tr>
<th>Test Year</th>
<th>Experience Category</th>
<th>Count of Operators</th>
</tr>
</thead>
<tbody>
<tr>
<td>2019</td>
<td>Automatic Steering</td>
<td>1</td>
</tr>
<tr>
<td>2019</td>
<td>High</td>
<td>2</td>
</tr>
<tr>
<td>2019</td>
<td>Low</td>
<td>3</td>
</tr>
<tr>
<td>2022</td>
<td>Automatic Steering</td>
<td>2</td>
</tr>
<tr>
<td>2022</td>
<td>High</td>
<td>5</td>
</tr>
<tr>
<td>2022</td>
<td>Low</td>
<td>7</td>
</tr>
</tbody>
</table>

Field Procedure

Data for this study was collected in the same field at the Clemson University EREC in November of 2019 and October of 2022. A sample of operators (N=16, N=12 for 2022 tests and N=4 for 2019 tests) volunteered to take part in the study, participants were given a survey to gauge their experience in peanut production. For tests in 2019 a FloRun 331 variety peanut was utilized, and tests in 2022 a Virginia type Emery variety peanut was utilized. Participants were given the opportunity to dig two to three practice plots of the same dimensions as those in the test. Both test years used a randomized block design;
operators were tasked with digging four randomly selected plots in 2019 testing and six randomly assigned plots in 2022 testing. Machinery utilized in the study include Case Maxxum 140 (CNH Industrial, Amsterdam, Netherlands) equipped with Trimble Autopilot™ (Trimble Navigation Limited, Sunnyvale, Cal.) and a KMC 2-38 (Kelley Manufacturing Co., Tifton, Ga.) peanut digger equipped with automated depth control (Kirk et al., 2016; Warner, 2015). Prior to starting at each plot, operators were lined up to the center of the plot using automatic steering and dug peanuts at a constant speed of 4.0 km hr⁻¹ (2.5 mi hr⁻¹) in 2019 and 3.2 km hr⁻¹ (2.0 mi hr⁻¹) in 2022. Conveyor speed was also controlled and set to match the tractor’s ground speed before the beginning of the test. An experienced peanut digging and harvesting equipment operator was utilized to supervise the tests as a test administrator. The test administrator was in the cab of the tractor for the duration of the test, to verify correct plot and operator assignments along with tractor operational parameters such as ground speed, engine speed, and conveyor speed. Location data at 1 Hz rate was recorded from the RTK receiver mounted to the tractor. Digging operations were conducted on 8 November 2019 and 28 October 2022. Figure 5 displays and example of a plot including points where tractor was actively digging peanuts, A-B line, and plot boundary. In the figure, there are no points recorded in the beginning of the plot, this is because the GPS position is on the roof and center of the tractor not the digger. Points are therefore shifted forward by roughly the distance between the peanut digger and the receiver.
Data Processing

Spatial analysis including merging of point and polygon data was conducted on ArcGIS Pro 3.1.2 (ESRI, Inc., Redlands, Cal.) and Haversine cross-track distance (Veness, 2022) calculations were conducted in Microsoft Excel (Microsoft Corp., Redmond, Wash.). Figure 6 displays the workflow for data analysis and programs used for each step. After the position and treatment data were extracted from the data log on the automated depth peanut digger control software, they were loaded into ArcGIS Pro, where repeated location, idle, and unknown digging status data was removed from the set. A-B line data and plot identification data were merged to the point data depending on their assignment.
and location, then data was exported to Microsoft Excel for Haversine cross-track distance calculations. Once distances were calculated, the data set was exported to JMP Pro 16 (SAS Institute Inc., Cary, NC) for statistical analysis and hypothesis testing. Where for main effect tests, an analysis of variance (ANOVA) was used to find any levels of significance and a Tukey-Kramer Honestly Significant Difference (Tukey HSD) test was used to make pairwise comparisons.

Figure 6: Data analysis workflow
Peanut Yield Measurement

Plots were laid out with two 0.96 m (38 in) m rows that measured 15.24 m by 0.96 m (50 ft by 3.2 ft). Plots were harvested using a 2 row Hobbs peanut combine (AMADAS Industries, Suffolk, VA). For tests in 2019, plots were combined four days after digging and in 2022 plots were combined six days after digging. The normalize for block/ year differences, the analysis was conducted based on yield loss, which were estimated using Equation (4), where the difference of the 90th percentile block yield and individual plot yield was used as yield loss. Plot weights were measured using an on-combine weighing system and samples were dried using a modified ASABE S410.3 Alternate Whole Pod Method (ASABE, 2020). Wet basis moisture content was calculated then yield was corrected to 10% MC_{wb}, this moisture content corrected yield was used to analysis.

\[ Y_{\text{loss}} = Y_{d90} - Y_{A} \]

Where,

\( Y_{d90} = \) 90th percentile block yield (kg-ha\(^{-1}\)),

\( Y_{A} = \) Actual plot yield (kg-ha\(^{-1}\)).

2.3.5 Statistical Analysis

For experiments testing an operator’s ability to find the true row center, an ANOVA (\(\alpha=0.05\)) was conducted using cross-track distance as the main dependent variable. Independent variables included the operator’s number, row orientation, and seeking
distance. Variables were tested for significant effects on the absolute cross-track distance and any interactions between independent variables. For both seeking distances, relative cross-track distances were tested for significant differences in their means from zero.

For experiments evaluating the effect of operator experience on mean absolute guidance line deviation and yield, an ANOVA (α=0.05) was also used to find main effects, and differences between groups were evaluated using Tukey-Kramer HSD. Dependent variables included mean absolute guidance line deviation for each plot and yield loss, estimated as described above. The independent variables include operator experience level (Automatic steering, High experience, low experience). Linear regressions were also developed to evaluate yield loss as a function of mean absolute deviation.

2.4 Results and Discussion

2.4.1 Experiment 1: Perceived Row Center

To evaluate how well the perceived or apparent row center aligned with the actual row center, the mean cross-track distance for each row orientation and distance combination were tested for differences from zero, which represents the actual row center. Means for each distance and row orientation combination are shown in Table 4. At the near distance, both the means for both row orientations were significantly different from zero (p=<0.0001, for both row orientations), with means of -12.1 cm (-4.8 in) and -11.1 cm (-4.4 in) for the North-South and East-West orientation, respectively. However, the far distance mean was not significantly different from zero for either row orientation (p=0.9221, East-West and p=0.182, North-South). Figure 7 and Figure 8 display scatter
plot with points along the x axis representing the distance from the row center at both near and far seeking distances. The dashed vertical lines signify the means for each row center and distance combination. Table 5 displays the means and standard deviations for each operator for each seeking distance and for both seeking distances combined.

Table 4. Relative Cross-Track Distance, by Seeking Distance and Row Orientation\[a\]

<table>
<thead>
<tr>
<th>Row Orientation</th>
<th>Seeking Distance</th>
<th>Mean ± Standard Deviation</th>
<th>Lower 95% CI</th>
<th>Upper 95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>East to West</td>
<td>Near</td>
<td>-11.1* ± 16.5</td>
<td>-16.2</td>
<td>-5.9</td>
</tr>
<tr>
<td>East to West</td>
<td>Far</td>
<td>0.2 ± 10.9</td>
<td>-3.2</td>
<td>3.6</td>
</tr>
<tr>
<td>North to South</td>
<td>Near</td>
<td>-12.1* ± 14.0</td>
<td>-16.4</td>
<td>-7.7</td>
</tr>
<tr>
<td>North to South</td>
<td>Far</td>
<td>-2.8 ± 13.3</td>
<td>-6.9</td>
<td>1.4</td>
</tr>
</tbody>
</table>

[a] Taken as the cross-track distance between the row center estimated from the A-B line and operator observed row center, relative to the side of the guidance line

*Indicates significant difference from zero, at (α=0.05)
Figure 7. Perceived row center for North-South plots
Figure 8. Perceived row center for East-West plots

Table 5: Cross-Track Distance Descriptive Statistics by Operator (N=24 per operator)\[a\]

<table>
<thead>
<tr>
<th>Operator #</th>
<th>Mean ± Standard Deviation, Near (cm)</th>
<th>Mean ± Standard Deviation, Far (cm)</th>
<th>Absolute Mean ± Standard Deviation, Overall (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-5.8 ± 14.5</td>
<td>6.6 ± 9.6</td>
<td>11.7 ± 6.6</td>
</tr>
<tr>
<td>2</td>
<td>-3.5 ± 13.6</td>
<td>4.5 ± 8.8</td>
<td>10.6 ± 5.1</td>
</tr>
<tr>
<td>3</td>
<td>-8.7 ± 13.0</td>
<td>0.4 ± 8.6</td>
<td>9.6 ± 7.6</td>
</tr>
<tr>
<td>4</td>
<td>-6.1 ± 11.3</td>
<td>0.4 ± 9.1</td>
<td>8.9 ± 6.1</td>
</tr>
<tr>
<td>5</td>
<td>-10.7 ± 12.5</td>
<td>-3.9 ± 7.0</td>
<td>9.3 ± 8.7</td>
</tr>
<tr>
<td>6</td>
<td>-26.5 ± 14.1</td>
<td>-13.2 ± 17.4</td>
<td>22.9 ± 12.3</td>
</tr>
<tr>
<td>7</td>
<td>-19.7 ± 15.5</td>
<td>-4.0 ± 12.6</td>
<td>15.8 ± 11.8</td>
</tr>
</tbody>
</table>

[a] Taken as the cross-track distance between the row center taken from the A-B line and operator observed row center, relative to the side of the guidance line

*Operators with the same letter indicate no significant differences at (α = 0.05)
The overall effects of seeking distance and row orientation were also evaluated relative to each other using the absolute cross-track distance. The overall effect of seeking distance was significant \((p < 0.0001)\), where the operator’s perception of the row center better matched the actual row center at the far distance \((32.3 \text{ m}, 106 \text{ ft})\). The mean cross-track distance at the near distance was 15.7 cm (6.2 in) and the mean for the far distance was 9.6 cm (3.8 in), these are displayed in Table 6 along with the overall absolute cross-track distances for both row orientations. Row orientation did not have a significant effect on mean cross-track distance \((p = 0.5042)\); however, this can be interpreted as operator’s mis-perceiving the row center, regardless of row orientation at a near distance. As seen in Table 4, Figure 7, and Figure 8; operators tended to perceive the row centerline to be south and west of the actual row centerline. For both row orientations at a near distance the means were both less than zero, signifying that distances were perceived to be south and west.

Further analysis on the canopy leaning direction was conducted, and solar direction and intensity information was retrieved from the National Renewable Energy Laboratory (NREL) Solar Position and Intensity (SOLPOS) calculator (NREL, 2023). This leaning of the plant canopy can also be caused by other factors such as wind direction, planting location, and row orientation. Data was entered for the experiment location and dates ranging from 1 September 2022, and 1 November 2022. This populated the prime solar azimuth for each day in that date range. The average azimuth was taken from this data and was found to be 181°. This azimuth falls in between the South-West and South-East quadrants and indicates the prime direction for solar intensity to the be roughly South. These results shows that the plant can grow to the direction of the highest solar intensity,
leading to the creation of a false row centerline. This false row centerline has the potential to cause an operator to deviate from the actual centerline during peanut digging operations and result in yield losses, no matter the row orientation. However, with operators gazing towards the horizon rather than the front of the tractor they may be less likely to deviate from the actual row center.

Table 6. Mean Absolute Cross-Track Distances for Testing Effects of Seeking Distance and Row Orientation

<table>
<thead>
<tr>
<th>Row Orientation</th>
<th>N</th>
<th>Seeking Distance</th>
<th>Mean ± Standard Deviation (cm)</th>
<th>Lower 95% CI*</th>
<th>Upper 95% CI*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Combined</td>
<td>84</td>
<td>Near</td>
<td>15.7 ± 10.8</td>
<td>13.4</td>
<td>18.1</td>
</tr>
<tr>
<td>Combined</td>
<td>84</td>
<td>Far</td>
<td>9.6 ± 7.5</td>
<td>8.0</td>
<td>11.3</td>
</tr>
<tr>
<td>East to West</td>
<td>84</td>
<td>Overall</td>
<td>12.2 ± 10.2</td>
<td>10.1</td>
<td>14.3</td>
</tr>
<tr>
<td>North to South</td>
<td>84</td>
<td>Overall</td>
<td>13.2 ± 9.3</td>
<td>11.1</td>
<td>15.3</td>
</tr>
</tbody>
</table>

[a] Taken as the cross-track distance between the row center taken from the A-B line and operator observed row center, not relative to the side of the guidance line

*at (α=0.05)

2.4.2 Experiment 2: Impact of Operator Experience on Mean Absolute Guidance Line Deviation and Recovered Yield

Influence of Operator Experience on Mean Absolute Guidance Line Deviation

The descriptive statistics for each operator included in the 2019 and 2022 peanut digging experiments, including RTK automated steering replications, can be seen in Table 7. The mean absolute deviation in Table 7 refers to the overall mean of the absolute cross-track distances for each point in each plot the assigned operator was digging. The average number of observations per plot was less in the 2019 tests compared to those in 2022,
primarily because the digging speed in the 2019 tests was faster than in 2022. Consequently, approximately four additional observations per plot were recorded during the 2022 tests.

Table 7: Peanut Digging Position Data Descriptive Statistics

<table>
<thead>
<tr>
<th>Operator</th>
<th>Year</th>
<th>Experience Level</th>
<th># of Plots Dug</th>
<th>Average Points per Plot</th>
<th>Mean Absolute Guidance Line Deviation ± Standard Deviation (cm)</th>
<th>Opinion: Performance vs Automatic Steering</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2022</td>
<td>Automatic Steering</td>
<td>6 23</td>
<td>3.751 ± 1.362</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>2022</td>
<td>Low</td>
<td>6 25</td>
<td>6.199 ± 3.651</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>2022</td>
<td>High</td>
<td>6 23</td>
<td>2.031 ± 1.149</td>
<td>Worse</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>2022</td>
<td>High</td>
<td>6 24</td>
<td>4.142 ± 2.937</td>
<td>Better</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>2022</td>
<td>High</td>
<td>6 22</td>
<td>8.523 ± 7.461</td>
<td>Worse</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>2022</td>
<td>Low</td>
<td>3 23</td>
<td>6.396 ± 4.344</td>
<td>Worse</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>2022</td>
<td>Low</td>
<td>6 23</td>
<td>11.032 ± 5.941</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>2022</td>
<td>High</td>
<td>6 23</td>
<td>6.671 ± 3.369</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>2022</td>
<td>Automatic Steering</td>
<td>6 24</td>
<td>3.677 ± 1.284</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>2019</td>
<td>High</td>
<td>4 17</td>
<td>5.149 ± 3.807</td>
<td>Worse</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>2022</td>
<td>Low</td>
<td>6 24</td>
<td>2.821 ± 0.711</td>
<td>Worse</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>2022</td>
<td>High</td>
<td>6 22</td>
<td>7.033 ± 4.766</td>
<td>Worse</td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>2022</td>
<td>Low</td>
<td>6 25</td>
<td>6.671 ± 3.012</td>
<td>Better</td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>2019</td>
<td>Low</td>
<td>6 22</td>
<td>4.605 ± 1.831</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>2019</td>
<td>Low</td>
<td>4 13</td>
<td>10.394 ± 5.982</td>
<td>Worse</td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>2022</td>
<td>Low</td>
<td>6 23</td>
<td>7.827 ± 5.983</td>
<td>Worse</td>
<td></td>
</tr>
<tr>
<td>17</td>
<td>2019</td>
<td>Low</td>
<td>6 23</td>
<td>5.777 ± 2.903</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>2019</td>
<td>Low</td>
<td>4 17</td>
<td>5.067 ± 3.279</td>
<td>Worse</td>
<td></td>
</tr>
<tr>
<td>19</td>
<td>2019</td>
<td>Automatic Steering</td>
<td>4 16</td>
<td>1.864 ± 1.668</td>
<td>*</td>
<td></td>
</tr>
</tbody>
</table>

*Only operators with previous peanut digging experience were given this question*

Figure 9 shows the mean absolute guidance line deviation, separated by automatic steering and operator experience level. This is based on all available data, without
segregation by test year or block as preliminary investigation indicated these did not affect the mean absolute deviation (p=0.3498 and 0.2799, respectively). The main effect of operator experience level on mean absolute guidance line deviation was significant (p=0.0004) and the mean absolute guidance line deviation (± standard deviation) was 3.3±1.6 cm (1.3±0.6 in), 5.1±4.0 cm (2.0±1.6 in), 7.6±4.6 cm (3.0±1.8 in) for automatic steering, high, and low experience levels respectively. Means comparison using Tukey’s HSD indicated significant differences between the low experience, and the levels high and automatic steering. However, no significant differences were observed between high experienced operators and automatic guidance. This indicates that, at least over the short plots examined in this study, a highly experienced operator can perform with the same level of mean absolute deviation as RTK corrected automated steering.

Figure 9. Mean Absolute Guidance Line Deviation by Level of Operator Experience*
*N=16, 44, 50 for “Automatic Steering”, “High”, and “Low” respectively. Error bars represent the 95% Confidence Interval of the Mean. Bars with same letter were not significantly different at the 0.05 level.
Influence of Operator Experience and Mean Absolute Guidance Line Deviation on Recovered Yield

Table 8 displays the yield descriptive statistics for each operator, separated by year if the operator participated in 2019 and 2022 tests. For Operator 6, there is no standard deviation for yield listed as there was only one plot of yield data available for this operator. Overall, that the difference in mean absolute guidance line deviation between levels of operator experience did not translate to differences in recovered yield, and no have a significant effect on recovered yield were observed at any experience level. Figure 10, shows the mean plot yield loss in kg ha\(^{-1}\) for each experience level for both test years and error bars representing 95% confidence interval at (\(\alpha=0.05\)).
<table>
<thead>
<tr>
<th>Operator</th>
<th>Year</th>
<th>Experience Level</th>
<th># of Plots Dug</th>
<th>Mean Yield ± Standard Deviation (kg/ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>2019</td>
<td>High</td>
<td>4</td>
<td>3445.7 ± 368.4</td>
</tr>
<tr>
<td>14</td>
<td>2019</td>
<td>Low</td>
<td>4</td>
<td>3357.3 ± 511.7</td>
</tr>
<tr>
<td>15</td>
<td>2019</td>
<td>Low</td>
<td>6</td>
<td>3067.4 ± 1199.2</td>
</tr>
<tr>
<td>16</td>
<td>2019</td>
<td>High</td>
<td>4</td>
<td>3447.2 ± 470.6</td>
</tr>
<tr>
<td>17</td>
<td>2019</td>
<td>Low</td>
<td>3</td>
<td>3455.5 ± 1351.1</td>
</tr>
<tr>
<td>18</td>
<td>2019</td>
<td>Low</td>
<td>4</td>
<td>3715.7 ± 434.8</td>
</tr>
<tr>
<td>19</td>
<td>2019</td>
<td>Automatic Steering</td>
<td>4</td>
<td>3762.3 ± 650.2</td>
</tr>
<tr>
<td>1</td>
<td>2022</td>
<td>Automatic Steering</td>
<td>6</td>
<td>2858.9 ± 658.2</td>
</tr>
<tr>
<td>2</td>
<td>2022</td>
<td>Low</td>
<td>6</td>
<td>2717.8 ± 1097.9</td>
</tr>
<tr>
<td>3</td>
<td>2022</td>
<td>High</td>
<td>6</td>
<td>2784.9 ± 1390.0</td>
</tr>
<tr>
<td>4</td>
<td>2022</td>
<td>High</td>
<td>6</td>
<td>3238.3 ± 1380.1</td>
</tr>
<tr>
<td>5</td>
<td>2022</td>
<td>High</td>
<td>6</td>
<td>2841.6 ± 1219.0</td>
</tr>
<tr>
<td>6</td>
<td>2022</td>
<td>Low</td>
<td>3</td>
<td>4247.5 ± 0*</td>
</tr>
<tr>
<td>7</td>
<td>2022</td>
<td>Low</td>
<td>6</td>
<td>2944.8 ± 1106.7</td>
</tr>
<tr>
<td>8</td>
<td>2022</td>
<td>High</td>
<td>6</td>
<td>3117.3 ± 960.9</td>
</tr>
<tr>
<td>9</td>
<td>2022</td>
<td>Automatic Steering</td>
<td>6</td>
<td>2784.08 ± 1403.4</td>
</tr>
<tr>
<td>10</td>
<td>2022</td>
<td>High</td>
<td>6</td>
<td>3441.1 ± 1264.6</td>
</tr>
<tr>
<td>11</td>
<td>2022</td>
<td>Low</td>
<td>6</td>
<td>3016.8 ± 904.0</td>
</tr>
<tr>
<td>12</td>
<td>2022</td>
<td>High</td>
<td>6</td>
<td>3192.7 ± 1126.0</td>
</tr>
<tr>
<td>13</td>
<td>2022</td>
<td>Low</td>
<td>6</td>
<td>3160.2 ± 1227.4</td>
</tr>
<tr>
<td>14</td>
<td>2022</td>
<td>Low</td>
<td>6</td>
<td>2995.5 ± 1173.4</td>
</tr>
</tbody>
</table>

*Operator 6 yield data unavailable*
A linear regression was used to evaluate the yield loss (relative to the 90\textsuperscript{th} percentile of each block) as a function of mean absolute guidance line deviation displayed in Figure 11. Results from the linear regression showed that for every cm of mean absolute guidance line deviation 95.5 kg ha\textsuperscript{-1} (216.3 lb ac\textsuperscript{-1} in\textsuperscript{-1}) of potential yield is lost. There was a large amount of scatter at all levels of deviation, but this correlation was found to be significant (\(p<0.0001\)).
Figure 11. Yield Loss (kg ha\textsuperscript{-1}) by Mean Absolute Guidance Line Deviation (cm). Estimated using Eq. (4), including data from both years.

2.4.3 Evaluation of the value of RTK Corrected Automatic Steering

One of the biggest barriers to entry in precision agriculture technologies for farmers is the costs of these systems. Depending on the machinery present on the farm and their access to base stations or cellular network streamed corrections, the costs of guidance systems can be upwards of $25,000 (McFadden et al., 2023; Vellidis et al., 2013). For reference, in the 2017 USDA Census of Agriculture the most prevalent sizes of farms producing peanuts in the State of South Carolina were those 101.2-201.9 ha (250-499 ac) and, 40.5-100.8 ha (100-249 ac), and 10.1-40.4 ha (25-99.9 ac). Each of these production area categories represents 23.1\%, 21.2\%, and 12.0\% of the total peanut producers in the State of South Carolina, respectively. McFadden et al. (2023) found that overall, in the United States for 2018 soybean production and 2019 cotton production, those operators in

36
the 4 quintile or greater by acreage had the highest adoption rates of automatic steering systems, 68% and 67% respectively.

Specific to peanut digging, one of the primary quantifiable values of using automatic steering is associated with the potential increase in recovered yield associated with reduced mean absolute guidance line deviation while using automatic steering. The results from this investigation indicate that an operator with less experience using automatic steering can perform at the same level, or better, compared to a high skilled operator steering manually (Figure 9). These deviations did not translate to measurable differences in yield losses between groups (Figure 10); however, mean guidance line deviation was found to be significantly correlated with yield losses (Figure 11), which is consistent with other works that showed automatic steering and mean guidance line deviation impacted yield losses (Ortiz et al., 2013; Roberson and Jordan, 2014; Santos et al., 2019; Vellidis et al., 2013).

One implication of this is that a lower skilled operator utilizing automatic steering could replace a high skilled operator (i.e., the primary producer). Figure 12 shows the impact of this labor replacement as a function of area harvested for typical peanut digger configurations. Wages used were drawn from USDA ERS national averages for agricultural equipment operator and farm managers, where agricultural equipment operators were defined as low skill level and were assumed a wage of $15.36 hr$^{-1}$ and high skill level operators were based on farm managers and were assigned a wage of $25.58 hr$^{-1}$ (Castillo and Simnitt, 2023). Effective field capacity was calculated for 2, 4, and 6 row peanut diggers on 96.5 cm (38.0 in) rows and travelling at a ground speed of 4.0 km hr$^{-1}$.
(2.5 mi hr⁻¹), using field efficiency of 85% (ASABE, 2017). This field efficiency is not listed in the ASABE standards but was estimated from similar implements, similar to (ASABE, 2011; Roberson, 2023). The value of the labor replacement increases linearly as a function of area harvested and ranged was $15.5 \text{ ha}^{-1}$, $7.7 \text{ ha}^{-1}$, and $5.2 \text{ ha}^{-1}$ for 2, 4, and 6 row diggers, respectively.

![Figure 12. Cost Savings for High vs Low Skill Operators](image)

While this analysis did not directly find significant differences in yield loss between experience groups, it is important to note yield losses were highly variable and are generally difficult to quantify. Additionally, considering the observed differences in mean absolute guidance line deviation between groups, coupled with the established relationship between deviation and yield, a deeper examination of the potential advantages of automatic steering is warranted. Figure 13 shows the payoff area (ha) for a farm to recover a $25,000 investment in automatic steering through additional recovered yield by providing high and
low skilled operators with an RTK corrected automatic steering system. This was estimated using the projected yield losses due to mean absolute guidance line deviation from Figure 11 [95.5 kg ha\(^{-1}\) cm\(^{-1}\) (216 lb ac\(^{-1}\) in\(^{-1}\))], combined with the difference in mean absolute guidance line deviation from each experience group and the mean absolute guidance line deviation for automatic steering. These differences in mean guidance line deviation were found to be 1.9 cm (0.75 in) and 4.4 cm (1.7 in) for high and low skilled operators respectively (Figure 9). This was then multiplied by the 10-year average cost of peanuts, $0.49 kg\(^{-1}\) (USDA, 2022a), resulting in a benefit of $89 ha\(^{-1}\) and $206 ha\(^{-1}\) for high and low experience operators, respectively. It was found that for providing high skilled operators with automatic steering technology, the payoff area was 281 ha (694 ac) and for providing that technology low skilled operators the payoff area was 121 ha (299 ac).

![Figure 13. Mean Payoff Area (ha) by Experience Level Through Yield Recovery by Using RTK Corrected Automatic Steering Systems](image-url)
Combining labor and yield benefits, Figure 14 presents the overall value of utilizing automatic steering for peanut digging. The value of labor replacement from a 4-row digger (Figure 12) was combined with comparative loss data from this and other studies to evaluate a range of potential outcomes. The 4-row peanut digger/inverter size was chosen as this was the most prevalent peanut digger size used by operators from the results of this study’s survey. Additional yield recovery values from Roberson and Jordan (2014) and Vellidis et al. (2013) were 508 and 515 kg ha\(^{-1}\) (average of two years), respectively. These studies both reported only the general benefit of automatic steering relative to manually steering but did not quantify operator experience or deviation. The additional yield recovery values shown for this study and Ortiz et al. (2013) were found as a function of guidance line deviation, combined with the difference in mean absolute guidance line deviation between low skill operators and RTK corrected automatic steering from this study [4.37 cm (1.7 in)]. For this study, the previously discussed additional yield recovered was 420 kg ha\(^{-1}\). Ortiz et al. (2013) offset the guidance line by 0 cm, 9 cm, and 18 cm, to simulate the impact of deviation from manually steering. Using their single-row conventional tillage results, the slope of the yield versus deviation line is 87.2 kg ha\(^{-1}\) cm\(^{-1}\). Combined with this study’s average deviation, this represents an additional yield recovery of 384 kg ha\(^{-1}\).
Figure 14. Combined labor and yield recovery savings for a four row peanut digger inverter. Projections based on labor replacement and various estimates of additional yield recovery. (a)Estimated using the deviation improvement between automatic steering and low-experience operators from this study, combined with the recovered yield estimated as a function deviation from the respective works (kg ha⁻¹ cm⁻¹). (b) Based on labor replacement plus general estimates of additional yield recovered from using automatic steering systems (kg ha⁻¹).

By applying the same peanut value of $0.49 kg⁻¹, and considering the combined labor replacement and additional yield recovery shown in Figure 14, the estimated area required to recover the initial investment of $25,000 for an RTK corrected automatic steering system ranged from 96 to 128 ha. This breakdown aligned closely with the method
used to estimate the additional yield recovery, with this study and Ortiz et al. (2013)
resulting in longer paybacks. It should also be noted these figures provide a general
estimate, based on the conditions and yield of the respective studies. Actual recovered yield
and labor replacement benefits will be site-specific. Additionally, the labor replacement
value does not account for time required to set up the digger and adjust conveyor speed,
digger depth, etc., which would require a more experienced operator. A higher skilled
operator would also be able to better monitor and identify issues quickly. However, a
smaller operation growing 40.5 ha (100 ac) of peanuts per year would still breakeven after
3.2 years, for any of the cases shown in Figure 14. This analysis also only considers use
only for peanut digging, but the system would likely be utilized for other operations.

2.4.4 Experimental Limitations

Both experiments utilized RTK GPS receivers for spatial data collection and high
spatial accuracies are important for the data to be robust for analysis. North American
Datum (1983) UTM Zone 17N was the projected coordinate system used for analysis in
both experiments. As previously discussed, RTK GPS systems have an inherent error of
±2.5 cm (0.98 in). This error was minimized on the part of the test administrator as any
points that had a status other than “RTK Fix” were removed for analysis, as these
accuracies are much lower at distances greater than ±2.5 cm (0.98 in). These steps were
taken to reduce propagation of these positional errors for robust analysis. Uncertainties
were found using methods from Turner et al. (2016) and De Bruin et al. (2008).
Another limitation for both experiments, was the small sample sizes used to make population generalizations, $N = 7$ was used for tests analyzing an operator’s ability to distinguish the actual row center and $N = 16$ was used for experiments testing an operator's ability to maintain a constant course while digging peanuts. Increasing the sample size would allow for more robust generalizability; however, field work of this nature presents practical challenges: larger sample sizes than those used in this study would complicate the coordination of participants and require the reservation of a substantial area for testing.

For experiments testing an operator’s ability to maintain a constant course, plots used for testing were planted using automatic steering systems and dug with those systems active and inactive. So, yield losses in this study are an underestimation for losses that would be experienced when planting with manual steering and digging with manual steering. Also in these tests, the only variable tested was the operator’s ability to maintain a constant course was test, variable such as each operator setting ground speed, conveyor speed, and digging depth were not analyzed and these variables could yield different results.

There are harvest conditions could influence yield losses that were not tested during this experimentation. These factors can include peanut type, variety, soil moisture content, row spacing, twin or single rows, and digger setup among others. These factors were not possible to test in this work and any of these factors could influence changes in results.

These tests also used data that was collected in 2019 and 2022, several factors remained consistent between years, however there was some variation due to biological and climactic variables that could not be controlled in this study. However, results for yield
in both years were normalized as a yield loss, where the basis for loss was the 90th percentile yield for each block in the randomized block design. Using this method for normalization, variation effects for test year could be eliminated.

2.5 Conclusions

This study evaluated several factors related to mean absolute guidance line deviation during peanut digging and how they impact yield. Results from experiments testing an operator’s ability to distinguish actual row center showed no effect of row orientation on off-tracking distances. However, the observed or apparent row center tended to be South and West of the actual row center. Seeking distance was also shown to have a significant effect, where operators were better able to identify the row center at the far distances. This effect of seeking distance may influence where the operator references when manually steering the tractor and cause them to deviate from the actual center which can effect yield losses.

For experimentation testing the effect of operator experience on mean absolute guidance line deviation during peanut digging operations, operator experience did not have any statistical effect on the recovered yield. However, results showed significant effects from experience level on the mean guidance line deviation; where absolute guidance line deviation was on average 4.4 cm (1.7 in) higher for low-experience operators compared to RTK corrected automatic steering. Utilizing yield benefits estimated from this and other works, combined with cost savings from labor replacement of a high experienced operator, a producer could expect a $25,000 automatic guidance system to be paid off after digging
between 96 and 128 ha. This payback is strictly based on yield losses due to deviation and labor replacement during peanut digging operations and does not consider other operations where RTK corrected automatic steering systems could be used to replace labor and guidance line deviations that could reduce the payback area.

Future work for peanut digging experiments could include expanding the number of operator experience levels such that a high, medium, and low experience level could be evaluated. Future works could also include different digging dates, where peanuts are less mature and test any contributions of yield loss from maturity, as well as expanded plot sizes analyze any full field effects.
CHAPTER 3. ASSESSING THE EFFECTS OF CANOPY TRAFFIC COMPACTION ON RECOVERED YIELD AND MOISTURE CONTENT IN PEANUTS

3.1 Introduction

Peanuts have a significant economic impact on the agriculture industry in the State of South Carolina. Between the years 2012 and 2022 an average of 35,000 ha (88,000 ac) of land was in peanut production and resulted in an average of 4,187 kg ha\(^{-1}\) (3,735 lb ac\(^{-1}\)) (USDA, 2022b). South Carolina ranks 6\(^{th}\) nationally for overall production, and is one of thirteen states in the United States that produces peanuts (USDA, 2022c). Peanuts are unique in the fact that they must be dug from the ground and inverted for combining operations to take place. With the additional investment and recurring costs needed to run these unique pieces of machinery, producers must maximize crop yields and product quality to keep their operations profitable. Several pieces of specialized machinery are required for peanut harvesting operations, this may constitute the removal and reinstallation of dual rear wheels on their tractor for various operations. This can be costly for the producer if they are to hire this process out to a local service provider and dangerous due to the weight of the wheels, tires, and occasionally ballasting fluid.

Clemson University Cooperative Extension guides recommend that peanuts be planted on 91.44 cm (36 in) to 96.52 cm (38 in) row centers when planting in single plant rows (Anco, 2021). However, this poses an issue for producers who utilize tractors with dual rear wheels for various operations on the farm. Dual rear wheels can only be used for peanut digging and inversion for 6 and 8 row models for additional traction and ballasting,
and they be spaced as such they only impact the row middles (KMC, 2015). If dual rear wheels are used on 96.5 cm (38 in) row centers without the use of wheel spacers, the outer wheels will compact two rows of peanuts prior to, or during the process of digging and inversion (Figure 15).

Figure 15. Visualization of rows affected by wheel traffic during peanut digging operations when using dual rear wheels without wheel spacers.
3.1.1  Impact of Wheel Traffic on Peanut Yield and Drying Processes

Peanuts are a versatile crop that can serve multiple functions to an operation. The biomass and forage from the plant can be used for animal feed, and the edible legume is used in a variety of ways. Sorensen et al. (2009), studied the effects of a midseason forage harvest in Virginia type peanuts on recovered pod yield. Their experiments involved harvesting the forage biomass at a 20 cm (7.87 in) at different combinations of 60, 90, and 120 days after planting. Some plots were also treated with a plant growth regulator (prohexadione calcium, PHDC). The study found significant differences in pod yield for plots where forage was harvested and plots that were produced traditionally. This study did not specifically address the issues of traffic compaction on the plant canopy, as the researchers used a hedge trimmer to harvest plant biomass.

Mowing and trimming of the plant canopy can be beneficial for the control of Sclerotinia blight in peanuts. Though not focused on the effects of traffic compaction on pod yield, Butzler et al. (1998) removed excess plant canopy with a tractor and rotary mower, these studies were conducted in 1993 and 1994. In this study, the mower was used to prune the top one-third of the plant canopy and were pruned 96 days after planting. This study found significant differences in yield between plots that were pruned and those that were not pruned. While the work did not study the effect of wheel traffic compaction on pod yield, the effect of wheel traffic from pruning operations can be related to a yield loss from canopy compaction.

The mechanical crushing of the plant canopy and biomass can also result in faster drying. This process is used widely in hay production, where mower conditioners crush the
plant material being mowed to speed the drying process and reduce the time between mowing and bailing operations. This mechanical conditioning process in hay production by using two rubber rollers that crush the plant material between cutting and ejection from the machine. This process has shown to have significant effects on the drying rate of many forage crops (Rotz et al., 1982). This mechanical crushing process can be likened to that during peanut digging operations with improper settings and dual rear wheels and canopy compaction occurs. The rows of plants compacted can dry differently from those surrounding.

3.1.2 UAS Windrow Volume Estimation

Using unmanned aerial system (UAS) orthographic imagery to find changes in heights of biomass has been used in several studies. Koc et al. (2023) used UAS imagery to estimate biomass yields in alfalfa plots by using two UAS flights to determine a base canopy height model and a cut canopy height model. This study found significance in the use of digital surface models (DSMs) to predict cut height for forage biomass harvested. Methods from Koc et al. (2023) are directly applicable to our study conducted, by using DSMs generated from UAS imagery to create height and volume models.

The use of DSMs generated from red, green and blue (RGB) as well as those from light detection and ranging (LiDAR) sensors has been used widely in forestry disciplines to estimate tree volumes in forest stands. Järsnstedt et al. (2012) used these sensors to generate a high accuracy DSM to estimate change in tree growth and volume in a forest.
stand. This study found that the use of this imagery is a viable option for estimating forest and tree volumes.

3.1.3 Windrow Drying

After digging and inverting peanuts into windrows, these are dried in-field utilizing ambient air drying. The pod moisture content is around 50% at the time of digging and inversion, however they are too wet to be combined for farmer’s stock peanuts at that point. To be efficiently combined, the moisture content should be between or below 20-30% (Ogejo, 2009). However, no studies have been conducted to find any changes in windrow drying rates due to compaction from tractor wheel traffic.

3.2 Objectives

The objective of this study was to evaluate the effects of canopy traffic compaction on recovered pod yield, windrow volume, and changes in drying rates. The study also evaluated the use of UAS orthographic imagery and DSMs for finding peanut windrow volumes and effects of wheel traffic on these volumes.

3.3 Materials and Methods

3.3.1 Experiment Location

This experiment consisted of two randomized block design tests, each with two treatments; conventionally dug plots and those subjected to wheel compaction just prior to digging. Experiments were conducted at Clemson University’s Edisto Research and
Education Center (EREC) in Blackville, SC (33.37 N, -81.33 W) during fall 2022 harvest. Two-row plots of a Virginia variety of peanut (Emery) planted on 97 cm (38 in) rows were used for these tests. Two independent tests were conducted in differing soil textures (light and heavy), and each test consisted of twelve plots; two treatments and six replications. Figure 16 and Figure 17 display the field layout for each soil type, color coded for compacted and normal plots along with their corresponding plot identification number. Plots were assigned treatments of compaction and non-compaction utilizing a randomized block design. Plot number 3402 was moved one plot north due to a sprayer wheel traffic rut adjacent to the plot.

Figure 16. Heavy soil texture plot layout
3.3.2 Field Procedure

A Case Maxxum 140 (CNH Industrial, Amsterdam, Netherlands) equipped with Trimble Autopilot™ (Trimble Navigation Limited, Sunnyvale, Cal.) and a KMC 2-38 peanut digger (Kelley Manufacturing Co., Tifton, Ga.) equipped with automated depth control (Kirk et al., 2016; Warner, 2015) was used in these tests. Tractor tires sizes were 480/80R46 in the rear and 380/85R34 in the front, both inflated to 207 kPa (30 psi) and filled with ballasting fluid.

Plots receiving the compaction treatment were subject to tractor wheel traffic prior to digging to simulate the effect of traffic compaction caused by the dual rear wheels, where both rows of the plot were compacted by wheel traffic. To simulate the compaction caused
by dual rear wheels, the guidance line was shifted 48 cm (19 in) to both sides of the normal path center for digging to compact the plant canopy with wheel traffic using automatic steering. Where the plant canopy was compacted in the opposite direction of digging, the A-B line was shifted left or right 48.3 cm (19 in), then driven forward to compact one row’s canopy. The A-B line was then shifted back to the actual row center and driven in reverse back to the head of the plot. Then the A-B line was shifted 48.3 cm (19 in) in the opposite direction of the first shift and driven forward to compact the second row’s canopy. This does not provide an exact representation of the compaction caused by dual wheels, as the ground pressure would be lower compared to the compaction in this study. In this process the guidance line was shifted left of normal by 48 cm (19 in), then driven forward to compact the right row’s canopy. Then the guidance line was shifted 48 cm (19 in) right of normal and driven rearward to compact the left row’s canopy. While this simulated the plant canopy being flattened by the tractor tires, as would occur with dual rear wheels, it does not necessarily provide an exact representation of the compaction caused by dual wheels, as the ground pressure would be a function of equipment weight and load distribution.

These tests were performed in the same field broken into plots for the application of treatments. The tests consisted of a heavy and light soil texture, and tests were performed on both soil textures. The light soil was comprised of 96.4% sand and 2.2% clay, and the heavy soil of 87.4% sand and 3.9% clay. Immediately after compaction operations were completed, all plots were then dug and inverted. Ground speed for digging plots was set at 3.2 km-hr⁻¹ (2 mi-hr⁻¹), which was also used for compacting plots. Figure 18 and Figure 19
display compacted and uncompacted plant canopies, respectively. All plots were dug using automatic guidance with automatic digger depth control active.

Figure 18: Compacted plant canopy
3.3.3 Windrow Volume Estimation

After digging, aerial imagery was taken using a DJI Mavic 2 Pro (DJI Inc, Shenzhen, China) with automatic guidance and camera control using Litchi (VC Technology Ltd., London, United Kingdom). Orthographic imagery were stitched and processed in OpenDroneMap (UAV4GEO, Berea, Ohio). Photos were taken at an altitude of 30 m (98 ft) and the flight recorded 545 useable images. Ten ground control points were used and georeferenced utilizing Emlid Reach RS+ (Emlid, Inc, Budapest, Hungary) RTK GPS units in projected coordinate system North American Datum 1983 UTM Zone 17N. The stitching was completed with a horizontal and vertical accuracy of 5.0 and 9.0
centimeters (2.0 and 3.5 inches) respectively. For this study only one flight was used for analysis, where this flight was conducted the day after digging operations were finished. This was done as the flight conditions immediately after digging were not conducive for flight.

Physical measurements of windrow dimensions were also taken after plots were dug and inverted. Qualities measured include windrow height, approximate taproot angle, and soil moisture content. Windrow heights and taproot angle measurements were taken at the beginning, middle, and end of each windrow; and soil moisture was measured at the middle of each windrow. These physical measurements were taken to evaluate differences in quality of digging and inversion and to provide ground truth data for comparison with UAS generated volume estimates.

After drone photos were stitched, orthographic photos and digital surface models were exported to ArcGIS Pro (ESRI, Inc., Redlands, Cal.) for analysis. The whole field shapefile was imported to ArcGIS Pro and separated into two layers separating the soil textures. Kriging was used to create a bare soil surface elevation model for volume measurement, where 25 points were placed on points with bare soil in the orthophoto to create an interpolated bare soil surface elevation model. This was done separately for each soil type and required as there was not a separate flight done to find bare soil elevations. The Polygon Volume tool, native to ArcGIS Pro, was used to measure windrow volumes from the DSM.

The Polygon Volume tool in ArcGIS Pro calculates the volume of each raster cell inside of a polygon, in this case the footprint of each windrow, by calculating the difference
between the bar soil surface elevation model and the elevation of the windrow in each raster cell. The volume of each raster cell in the polygon is added together and outputs a polygon volume. After finding windrow volumes, data was exported to Microsoft Excel (Microsoft Corp., Redmond, Wash.) for plot analysis. Before combining, three height measurements were taken on each windrow to have a basis of comparison for windrow volumes from UAS imagery. These ground-truthed plot volumes were calculated for each plot using Equation (5) and compared with volumes estimated in ArcGIS Pro. These ground-truthed volumes use the cross-sectional area of the plot and the average of 3 windrow height measurements to calculate the volume as a rectangular prism. These volumes give a base measurement to assess the feasibility of utilizing UAS orthographic imagery for windrow volume estimations. Figure 20 displays the workflow for data import, export, and analysis.

\[ V_{WR} = W \times L \times \frac{\sum(H_1, H_2, H_3)}{3} \]  

(5)

Where,

\( V_{WR} \) = Windrow volume, ground-truthed (m³),

\( W \) = Width of windrow (m),

\( L \) = Length of windrow (m),

\( H_x \) = Windrow height (m).
Figure 20. Data analysis workflow

Figure 21 displays the bare soil elevations that were estimated using the Kriging method. The results from this analysis were used as a baseline to calculate the volumes of each windrow shown in Figure 22. These models include the alley-ways that were cut to separate each plot, as in some plots plant material was in the middle of the alley after the tractor stopped digging and the digger was lifted causing some material to bunch in the middle of the alley.
Figure 21. Estimated bare soil elevation for heavy soil texture
3.3.4 Yield and Moisture Content Measurement

Plots were harvested using a two-row Hobbs combine (AMADAS Industries, Suffolk, VA) and were combined six days after digging. The pod yield for each plot was generalized to kg-ha⁻¹ (lb-ac⁻¹) using the yield and area of each plot. A sub-sample of pods from each plot were taken at the time of combining for moisture analysis, these samples were then dried using a modified ASABE S410.3 Alternate Whole Pod Method (ASABE, 2020). This yield was adjusted to 10% moisture content and was used for all reporting and statistical analyses shown herein.
As-dug moisture content samples of approximately 750 g (1.65 lb) were taken from adjacent plots not involved in the test for each soil texture. These were used to characterize initial moisture content for each soil texture.

3.3.5 Statistical Analysis

Statistical analyses were conducted in JMP Pro 16 (SAS Institute LLC., Cary, NC), where main effects were evaluated using an analysis of variance (ANOVA) and pooled t-test. In this analysis the independent variable analyzed was canopy compaction; dependent variables tested included plot yield, windrow volumes, and final moisture content at the time of combining. For the analysis on the effects on wheel traffic compaction on windrow volume, these were done using the measurements from the ground-truthed windrow volumes. This was done as the methods for using UAS imagery to determine windrow volume is experimental. Linear regressions were also developed for final moisture content by windrow volume.

3.4 Results and Discussion

3.4.1 Windrow Volume

Method Comparison

Table 9 displays the windrow volumes for each plot along with identifiers for soil texture and treatment, measured using both ground-truthed and UAS orthographic imagery windrow volume measurement methods, along with the inversion quality for each windrow. Inversion quality was classified as “good” inversion is a taproot angle less than
or equal to 15°, and “bad” inversion is a taproot angle greater than 15°. Taproot angle is the angle at which the taproot of the plant is pointing where at 0° is the taproot pointing perfectly upward towards the sky.

<table>
<thead>
<tr>
<th>Soil Texture</th>
<th>Treatment</th>
<th>Windrow Volume, UAS Imagery (m³)</th>
<th>Windrow Volume, measured windrow heights (m³)</th>
<th>Difference Between Models (m³)</th>
<th>Inversion Quality</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heavy</td>
<td>Compacted</td>
<td>5.319</td>
<td>3.288</td>
<td>2.031</td>
<td>Bad</td>
</tr>
<tr>
<td>Heavy</td>
<td>Compacted</td>
<td>3.330</td>
<td>3.783</td>
<td>-0.453</td>
<td>Bad</td>
</tr>
<tr>
<td>Heavy</td>
<td>Compacted</td>
<td>2.910</td>
<td>6.352</td>
<td>-3.442</td>
<td>Bad</td>
</tr>
<tr>
<td>Heavy</td>
<td>Compacted</td>
<td>4.041</td>
<td>4.802</td>
<td>-0.761</td>
<td>Bad</td>
</tr>
<tr>
<td>Heavy</td>
<td>Compacted</td>
<td>4.836</td>
<td>5.655</td>
<td>-0.819</td>
<td>Good</td>
</tr>
<tr>
<td>Heavy</td>
<td>Compacted</td>
<td>3.068</td>
<td>4.012</td>
<td>-0.944</td>
<td>Good</td>
</tr>
<tr>
<td>Heavy</td>
<td>Normal</td>
<td>4.677</td>
<td>3.360</td>
<td>1.317</td>
<td>Bad</td>
</tr>
<tr>
<td>Heavy</td>
<td>Normal</td>
<td>6.250</td>
<td>5.168</td>
<td>1.082</td>
<td>Bad</td>
</tr>
<tr>
<td>Heavy</td>
<td>Normal</td>
<td>7.768</td>
<td>8.672</td>
<td>-0.904</td>
<td>Bad</td>
</tr>
<tr>
<td>Heavy</td>
<td>Normal</td>
<td>3.991</td>
<td>5.543</td>
<td>-1.552</td>
<td>Bad</td>
</tr>
<tr>
<td>Heavy</td>
<td>Normal</td>
<td>3.943</td>
<td>7.106</td>
<td>-3.163</td>
<td>Bad</td>
</tr>
<tr>
<td>Heavy</td>
<td>Normal</td>
<td>5.253</td>
<td>5.675</td>
<td>-0.422</td>
<td>Bad</td>
</tr>
<tr>
<td>Light</td>
<td>Compacted</td>
<td>5.359</td>
<td>5.235</td>
<td>0.124</td>
<td>Bad</td>
</tr>
<tr>
<td>Light</td>
<td>Compacted</td>
<td>5.258</td>
<td>4.014</td>
<td>1.244</td>
<td>Bad</td>
</tr>
<tr>
<td>Light</td>
<td>Compacted</td>
<td>6.823</td>
<td>4.012</td>
<td>2.811</td>
<td>Good</td>
</tr>
<tr>
<td>Light</td>
<td>Compacted</td>
<td>6.501</td>
<td>2.360</td>
<td>4.141</td>
<td>Good</td>
</tr>
<tr>
<td>Light</td>
<td>Compacted</td>
<td>5.035</td>
<td>2.935</td>
<td>2.100</td>
<td>Good</td>
</tr>
<tr>
<td>Light</td>
<td>Compacted</td>
<td>6.742</td>
<td>3.128</td>
<td>3.614</td>
<td>Good</td>
</tr>
<tr>
<td>Light</td>
<td>Normal</td>
<td>5.191</td>
<td>5.617</td>
<td>-0.426</td>
<td>Bad</td>
</tr>
<tr>
<td>Light</td>
<td>Normal</td>
<td>7.043</td>
<td>4.857</td>
<td>2.186</td>
<td>Good</td>
</tr>
<tr>
<td>Light</td>
<td>Normal</td>
<td>7.682</td>
<td>6.214</td>
<td>1.468</td>
<td>Good</td>
</tr>
<tr>
<td>Light</td>
<td>Normal</td>
<td>5.554</td>
<td>6.268</td>
<td>-0.714</td>
<td>Good</td>
</tr>
<tr>
<td>Light</td>
<td>Normal</td>
<td>6.398</td>
<td>4.854</td>
<td>1.544</td>
<td>Good</td>
</tr>
<tr>
<td>Light</td>
<td>Normal</td>
<td>6.689</td>
<td>5.427</td>
<td>1.262</td>
<td>Good</td>
</tr>
</tbody>
</table>

The applicability of using UAS imagery to estimate windrow volume was done by comparing the measured volume calculated in Equation (5), and the windrow volumes
found with UAS imagery analysis. This analysis used the UAS imagery as a basis for change, when calculating percentage differences. Mean percentage differences and windrow volumes between methods by treatment and soil texture are shown in Table 10. In heavy soil textures, the UAS imagery tended to estimate a lower windrow volume compared to volume derived from windrow height measurements. The opposite trend was observed for the light soil texture. The greatest difference between models was seen for plots that were compacted by wheel traffic, where the average differences were 39.3%. Plots that were normally harvested tended to have better agreement with average differences between -11.4% and 13.8%. Part of this difference can be attributed to the relatively small windrow volumes and the additional non-uniformity in compacted windrows. However, no statistical test was conducted to prove these observations.

<table>
<thead>
<tr>
<th>Soil Texture</th>
<th>Treatment</th>
<th>Mean Windrow Volume, Ground-Truthed (m³)</th>
<th>Mean Windrow Volume, UAS Imagery (m³)</th>
<th>Average Percent Difference (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heavy</td>
<td>Compacted</td>
<td>4.6</td>
<td>3.9</td>
<td>-18.7</td>
</tr>
<tr>
<td>Heavy</td>
<td>Normally Dug</td>
<td>5.9</td>
<td>5.3</td>
<td>-11.4</td>
</tr>
<tr>
<td>Light</td>
<td>Compacted</td>
<td>3.6</td>
<td>6.0</td>
<td>39.3</td>
</tr>
<tr>
<td>Light</td>
<td>Normally Dug</td>
<td>5.5</td>
<td>6.4</td>
<td>13.8</td>
</tr>
</tbody>
</table>

Effects of Wheel Traffic

It was found that canopy compaction from tractor wheel traffic had a significant effect in light soil textures (p=0.003) on the windrow volume at the time of digging but was found to not be significant in heavy soil textures (p=0.179). Table 11 displays the mean windrow volume using the ground-truthed method for the two wheel-traffic treatments,
separated by soil textures, along with connecting letters to signify any significant differences at (α=0.05). Windrows in the light soil texture had a larger volume compared to those plots in the heavy soil texture. The windrow volumes for light soil texture compacted plots were on average 65% of their normally dug counterparts (p=0.003). A similar trend was seen in heavy soil texture plots, but the difference was not significant (p=0.179). During the canopy compaction process the vine structure of the plant canopy was flattened and caused the windrows to be smaller than those in normally harvested plots.

Table 11. Mean and 95% Confidence Intervals (α=0.05) for Windrow Volume for Each Treatment, by Soil Type

<table>
<thead>
<tr>
<th>Soil Texture</th>
<th>Treatment</th>
<th>Mean*</th>
<th>Lower 95%</th>
<th>Upper 95%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heavy</td>
<td>Normal</td>
<td>5.921</td>
<td>4.023</td>
<td>7.816</td>
</tr>
<tr>
<td>Heavy</td>
<td>Compacted</td>
<td>4.649</td>
<td>3.412</td>
<td>5.885</td>
</tr>
<tr>
<td>Light</td>
<td>Normal</td>
<td>5.540</td>
<td>4.886</td>
<td>6.193</td>
</tr>
<tr>
<td>Light</td>
<td>Compacted</td>
<td>3.614</td>
<td>2.542</td>
<td>4.686</td>
</tr>
</tbody>
</table>

*Uppercase and lowercase letters represent means comparisons for heavy and light soil textures, respectively. Means with different letters in a given soil texture signify significant differences at (α=0.05)

3.4.2 Recovered Yield

Impact of Wheel Traffic on Recovered Yield

One of the primary motivations behind this investigation was the potential of increased yield losses due to wheel traffic compaction prior to digging, either due to plant movement or additional resistance when pulling the peanuts through the soil. Table 12 displays the mean plot yield for each soil texture and treatment combination, along with the 95% confidence intervals at (α=0.05). It was found that there was no significant
difference (p=0.1812 heavy soil texture, and p=0.2878 for light soil textures) in recovered yield due to canopy wheel traffic compaction, for either soil texture. While no significant differences in yield were observed, compacted plots had a lower recovered yield than those that were normally harvested, for both soil textures.

Table 12. Mean Plot Yields 95% Confidence Intervals (α=0.05) by Soil Texture and Treatment Combination

<table>
<thead>
<tr>
<th>Soil Texture</th>
<th>Treatment</th>
<th>Mean</th>
<th>Lower 95% (kg ha⁻¹)</th>
<th>Upper 95%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heavy</td>
<td>Normal</td>
<td>5987.89 A</td>
<td>4934.19</td>
<td>7041.59</td>
</tr>
<tr>
<td>Heavy</td>
<td>Compacted</td>
<td>5171.21 A</td>
<td>4159.35</td>
<td>6183.06</td>
</tr>
<tr>
<td>Light</td>
<td>Normal</td>
<td>2384.94 a</td>
<td>1664.20</td>
<td>3105.67</td>
</tr>
<tr>
<td>Light</td>
<td>Compacted</td>
<td>2025.72 a</td>
<td>1629.40</td>
<td>2422.04</td>
</tr>
</tbody>
</table>

*Uppercase and lowercase letters represent means comparisons for heavy and light soil textures, respectively. Means with different letters in a given soil texture signify significant differences at (α=0.05)*

In a practical production application, these yield losses would not be seen for the entire crop harvested. In this test, where canopy compaction was evaluated, two out of two rows in the plot were compacted. Canopy-compacting wheel traffic would only compact two out of six rows in a six-row digger assembly, and two out of eight rows on an eight-row digger assembly, this is visualized in Figure 15. Therefore, in practical applications, with a six-row digger only 1/3 of the losses shown in this study would be expected, and on an eight-row digger only 1/4 of these losses would be expected.

3.4.3 Moisture Content

Other concerns due to the compaction of the plant canopy include the drying rates of compacted rows compared to those that were harvested normally. The study analyzed the final moisture in heavy and light soil texture plots with compaction treatments. For
characterization, the at-digging pod moisture contents were 52% and 45% for light and heavy soil textures respectively. The compaction of the plant canopy had a significant (p=0.0002) impact on the at-harvest kernel moisture content in light soil texture plots, where the compacted plots had moisture content 3.4 points lower at the time of harvest. The differences were not significant in heavy soil texture plots (p=0.1569), but a similar trend was seen where compacted plots had a lower moisture content at harvest. The mean moisture content at combining and 95% confidence intervals at (α=0.05) are displayed in Table 13 by soil texture and treatment combination.

<table>
<thead>
<tr>
<th>Soil Texture</th>
<th>Treatment</th>
<th>Mean*</th>
<th>Lower 95%</th>
<th>Upper 95%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heavy</td>
<td>Normal</td>
<td>17.0 A</td>
<td>15.4</td>
<td>18.6</td>
</tr>
<tr>
<td>Heavy</td>
<td>Compacted</td>
<td>15.4 A</td>
<td>13.8</td>
<td>17.0</td>
</tr>
<tr>
<td>Light</td>
<td>Normal</td>
<td>18.1 a</td>
<td>17.2</td>
<td>19.1</td>
</tr>
<tr>
<td>Light</td>
<td>Compacted</td>
<td>14.7 b</td>
<td>13.7</td>
<td>15.7</td>
</tr>
</tbody>
</table>

*Uppercase and lowercase letters represent means comparisons for heavy and light soil textures, respectively. Means with different letters in a given soil texture signify significant differences at (α=0.05)

Regression analysis showed that ground-truthed windrow volume was a significant predictor of harvested moisture content in light soil textures (p=0.0062) but was not significant for heavy soil textures (p=0.3146). However, the same relationship was seen in heavy soil textures as those in light soil textures where, as the windrow volume increases the moisture content increases. Figure 23 and Figure 24 display the scatter plots of moisture content at harvest by windrow volume for light and heavy soil textures. These trends show that the larger windrows at digging, ultimately had the highest kernel moisture contents at combining.
Figure 23. Windrow volume by harvested moisture content. (For light soil texture N=12)

\[ y = 1.1851x + 10.998 \]
\[ R^2 = 0.5443 \]

Figure 24. Windrow volume by harvested moisture content. (For heavy soil texture N=12)

\[ y = 0.367x + 14.256 \]
\[ R^2 = 0.1008 \]
3.5 Conclusions

This study represents a preliminary investigation into the potential impact of not removing the tractor real duals prior to peanut digging. It also demonstrated the use of UAS imagery and DSMs has the potential to provide useful information for making production decisions by estimating windrow volume, especially when windrow volumes are larger. Although this study did not show any significant effects due to wheel traffic canopy compaction on recovered yield, a negative trend in yield was seen for plots that were compacted by tractor wheel traffic. In light soils significant effects from wheel traffic compaction were found on windrow volume (average of 1.9 m$^3$ lower) and kernel moisture content at combining (average 3.4 points higher). Along with a significant relationship between kernel moisture content at combining by the ground-truthed windrow volume. Similar trends were found in these variables for heavy soil textures; however, they were not significant.

There is potential in future research to investigate trends between windrow volumes and factors such as moisture content, yield, and product quality. These experiments were limited in some factors including orthographic imagery was only taken after digging, future works should include imagery for after digging, before combining, and after combining to create better fit models. Other variables to test can include different sizes of machinery and tire sizes and actual application of digging and inverting peanuts on a machine equipped with dual rear wheels that would compact the plant canopy. Another improvement for future work would be to expand the plots size to find effects due to canopy traffic compaction on a larger scale.
CHAPTER 4. PEANUT WINDROW DRYING CALCULATOR: A WEB APPLICATION FOR EXTENSION AND OUTREACH

4.1 Introduction

Peanuts (*Arachis hypogaea* L.) are a unique row crop cultivated in the southern and western United States, Latin America, Asia, Africa, the Middle East, and other places around the world (USDA, 2022d). They are unique relative to other grains and oilseeds in that the main product of the plant develops under the soil media and is harvested utilizing several pieces of machinery including tractors, digger/shaker/inverters, and combines. During digging, the entire plant is removed from the ground and inverted into a windrow. Typically, moisture content of the pods right after harvested ranges 45-55% wet basis (Ogejo, 2009). However, peanut combines will not separate pods from plants well at high moisture contents, and ultimately need to be dried to around 10% for safe storage. Typically, peanuts are allowed to field dry (cure) in windrows to about 18%-24% (Young, 1977).

Predicting suitable moisture content to initiate combining can be extremely problematic as the windrows are exposed to weather conditions such as high humidity, precipitation, and freezing temperatures. These are critical as the product can be damaged in the field before a producer is able to complete harvesting their crop. Producers are challenged in late peanut harvesting season to balance the risks in operations such as cold weather injury, scheduling digging and combining operations, suitable field workdays, and the cost of drying high moisture products at buying points. Decision support tools can
consider these issues and challenges and pair them with forecasts, current, and historical data to support producers in making agricultural management decisions.

For other row crops such as corn, there is a general trend of decreasing harvest moisture content over the course of the season (Martinez-Feria et al., 2019) and (Turner et al., 2019). However, when peanuts are dug and windrowed to be cured, the plant is still living when it comes out of the ground. So dug moisture content tends to be the consistent across the harvest season and variable with the moisture content of the surrounding soil (Dorner, 2008). However, cooler weather during the later fall peanut harvesting season results in lower drying potential later in the season compared to drying potential for warmer and more arid conditions during the early harvest season. This will result in either longer drying times or combining higher moisture peanuts. Figure 25 shows the mean incoming moisture content for the course of the harvest season for a South Carolina Buying point (Kendall Kirk, Clemson University, unpublished data, 1 Jul 2023) and illustrates this trend.
An additional consideration for late season harvest is cold weather injury, which refers to kernel damage that occurs when high moisture content peanuts are exposed to near or below freezing temperatures. Peanuts are most susceptible to injury the day they are dug, as this is point at which the crop is at its highest moisture content (Singleton and Pattee, 1997) and (Warren, 2023). Freeze damage can cause splits in the kernels, which makes them more susceptible to mold and aflatoxin growth. This can increase the percentage of damaged kernels and change the segregation of the peanuts being sold substantially affecting price received by the farmer. Much like grain crops such as corn and soybeans that are inspected and assigned a grade, peanuts are inspected and assigned a segregation. For peanuts to drop from Segregation 1, they must have no more than 3.49%
damaged kernels and be free from mold intrusion. For those with greater than 3.49% damaged kernels and free from mold intrusion, they are considered Segregation 2. For peanuts with any presence of mold, they are classified as Segregation 3 (USDA, 2023a). In 2021, the value of Segregation 1 Runner variety peanuts was $351.28 per ton, and $124.21 per ton for Segregation 2 and 3 (USDA, 2021) and (Kirk et al., 2021). It is critical for producers to consult weather forecasts and schedule digging and harvesting operations around times of critical temperature to avoid injury, which can result in a 50% loss in value per ton.

Windrow drying and curing simulations are not a new concept, Young (1977) developed a simulation model for drying peanuts in windrows. Their simulations were based on results from thin-layer drying models and were fit to drying peanuts in inverted windrows. However, their approach for predicting moisture content increases from rainfall were not adequate for that actual rewetting experienced in the field. Steele and Wright (1981) developed a computer simulation model for windrow drying of inverted peanuts, which was the basis of the web application developed as part of this work. This model uses the difference between the ambient conditions and conditions in equilibrium with the crop curing in the field, paired with a drying rate to determine the amount dried for each interval. In this model, when the equilibrium relative humidity (ERH) of the air is less than the ERH of the peanuts, drying will occur. Sub-routines in the overall model account for the increase in pod moisture content due to rainfall. Other sub-routines in their model consider that after rewetting, the crop will dry faster for a short period of time, they refer to this as a recovery period. Field data was used to validate their model, which had a root mean square error of
±1.7%\textsubscript{d.b.} to ±2.7%\textsubscript{d.b.} for windrowed and inverted peanuts curing for up to 12 days. Steele and Wright (1981) utilized equilibrium air temperature and wet-bulb depressions to determine drying. Most recent works represent moisture relationships using equilibrium moisture content (EMC), and in this work the logic from Steele and Wright (1981) was adapted to this format.

Precision agriculture encompasses many areas with the goal of optimizing products, timing, rates, and placement ultimately making a producer’s operation more profitable. One of these areas focuses on decision support systems that use historic and forecasted data to ease decision making on the part of the producer. These systems aggregate data from various aspects of the farm and assist the producer in making management decisions, scheduling operations, and the strategic sale of excess production (Turner, 2018). When developing decision tools, previously developed models such as those for forecasting the drying of windrowed and inverted peanuts can be paired with current data to improve reliability.

4.2 Objectives

The objective of this work was to develop a web application that estimates field drying of windrowed peanuts based on the local weather forecast. The goal of this tool was to assist peanut producers in decision making related to scheduling peanut digging and combining operations. In addition to estimating dry-down, a warning system was incorporated to identify conditions and predict where cold weather injury may occur.
4.3 Materials and Methods

4.3.1 Review of Related Equations

One approximation for field drying over time is to multiply the difference between the current moisture content and EMC by a drying constant (Gao et al., 2021; Martinez-Feria et al., 2019; Steele and Wright, 1981).

\[
\frac{dMC_{wb}}{dT} = -K(MC_{wb} - EMC_{wb})
\]

(6)

Where,
- \(MC_{wb}\) = Moisture content (% w.b.),
- \(T\) = Time (hr),
- \(K\) = Drying parameter (hr\(^{-1}\)),
- \(EMC_{wb}\) = Equilibrium moisture content (% w.b.).

The drying constant is related to local climate and ambient conditions (e.g., wind, temperature, RH, solar radiation). In context field drying has been most studied for maize; however, it is not well studied for peanuts. An approximation for drying constant from Yang et al. (2007), used in a thin layer peanut drying model is:

\[
K = 3.373 \times \exp\left(-\frac{4003}{T_{abs}}\right)
\]

(7)

Where,
- \(K\) = Drying constant (hr\(^{-1}\))
- \(T_{abs}\) = Temperature (Kelvin)

The rewetting or increase in moisture that occurs after rainfall was approximated by Steele and Wright (1981) using the rainfall intensity. Bounds were placed on the equation, so the maximum final moisture content was limited to 120%d.b. (54.5%w.b.).
This equation considers the rainfall intensity for an hour interval to calculate the moisture content gained due to rainfall during that hour.

\[ \Delta M = 0.113 \sqrt{R} \]  

(8)

Where,
\[ \Delta M = \text{Change in moisture content (\%, w.b.)}, \]
\[ R = \text{Rainfall intensity (cm/hr⁻¹)}. \]

The EMC as a function of temperature and relative humidity are defined by ASABE Standard D245.7 (ASABE, 2021). For whole pod peanuts this relationship can be represented using the Modified Oswin Equation with the constants below:

\[ EMC_{db} = \left(8.6588 + (-0.057904 \times T_c)\right) \times \left(\frac{RH}{1 - RH}\right) \frac{1}{2.6204} \]  

(9)

Where,
\[ EMC_{db} = \text{Equilibrium moisture content (\%, d.b.).} \]
\[ T_c = \text{Temperature (Celsius),} \]
\[ RH = \text{Relative humidity (\%).} \]

Dry basis moisture content can be converted to the more common wet basis moisture content using:

\[ MC_{wb} = \frac{100 \times MC_{db}}{100 + MC_{db}} \]  

(10)

Where,
\[ MC_{wb} = \text{Moisture content (\%, w.b.)} \]
\[ MC_{db} = \text{Moisture content (\%, d.b.)} \]
The previous relationships are based on whole pod moisture. This can be related to the kernel moisture by the following relationship from Kirk and Fogle (2016).

\[
Kernel_{MC} = 0.5464 \times Pod_{MC}^{1.1855}
\]  

(11)

Where,

- \( Kernel_{MC} \) = Kernel moisture content (% w.b.),
- \( Pod_{MC} \) = Pod moisture content (% w.b.).

4.3.2 Initial Development

The application was developed incrementally developed and tested in several different formats to ensure consistent predictions and forecasting. The initial implementation was performed in MATLAB R2021a (MathWorks, Inc., Portola Valley, Cal.), before transitioning to Microsoft Visual Studio Code (Microsoft Corp., Redmond, Wash.) for the final web application. The web application programming was written in Javascript, and the user interface was written in HTML. For the first several iterations, the static weather datasets were used to assess the functionality of the subroutine logic in the model. Following initial development, the web application was debugged and compared to the MATLAB implementation using the same static datasets and a local live server, after which the model inputs were switched to read weather data from an application programming interface (API).

4.3.3 Interface Development

The interface was developed to be user-friendly and cross-platform compatible (e.g., desktops, laptops, tablets, and smartphones). A screen capture from a desktop web
browser of the web application home page is shown in Figure 26. General information about EMC, ambient air drying, and the functionality of the models are provided above the user inputs. User inputs include a digging date, which can be a previous date, current date, or future date. The functionality for picking a digging date was implemented so the user can input either when they dug their crop or when they plan to do so. By inputting a future or previous digging date, the user can forecast when they will reach a moisture content where combining operations can commence or to find any impending dangers of cold weather injury. However, if the user picks a date past the current day the forecast is limited to 15 days past the current date. The user will also input a ZIP code; this is used to retrieve a site-specific weather forecast for the field location.

![Figure 26. Web application home page screen capture.](image)

Peanuts do not follow the same relationship of a decline in moisture content over the course of the harvest season, the product remains in the soil over the course of the harvest season so they will not dry as the season progresses. To consider these characteristics, the user may also choose from different drying rates, the include fast,
normal, slow, and custom. The interface defaults to the normal option as this is derived from known data sets; however, the user has the option to pick a slower, faster, or input their own custom drying rate. The user also inputs an initial as-dug whole pod moisture content, which is typically in the range of 50%\textsubscript{w.b.} (Ogejo, 2009). For each drying interval the tool converts this whole pod moisture content to kernel moisture content using data found in Kirk and Fogle (2016).

The last user input for the use of the tool is optional, but especially useful for evaluating the potential for cold weather injury during later harvest. These inputs are for the built-in highlighting rules. The user inputs a temperature and moisture content thresholds and if there are any temperatures lower and moisture contents higher than the inputs, the application will highlight those intervals on the graph with red bars and the rows in the table orange. Default values for each input are normal for drying rate, the current date for digging date, 50%\textsubscript{w.b.} for initial moisture content, and for highlighting rules 34°F and 14%\textsubscript{w.h.}.

The developed web application is hosted on the Clemson University Precision Agriculture: Calculators and Web Applications web page and is accessible at: https://precisionag.sites.clemson.edu/Calculators/Peanut/WindrowDrying/. The process for using the application is shown in Figure 27, where the user navigates to the Clemson University Precision Agriculture website and selects the “calculators” option, then opens the Windrowed Peanut Drying Forecaster. The user then enters the ZIP code of the field they would like to forecast drying in, a starting moisture content, selects a drying rate, and
selects a digging date. If the user does not change the digging date, then it defaults to the current date where the user has the application open.

Figure 27. Process for using the developed web application.

This application relies on accurate weather forecasts to calculate EMC and predict dry-down from the moisture content differential. Based on the provided dates and zip code,
historic/forecast weather data is pulled from the Visual Crossing (Visual Crossing Corp., Reston, Virg.) weather API. This API service provides historical weather data and up to a 15-day hourly forecast that includes temperature, relative humidity, precipitation probability and intensity, along with cloud cover and other characteristics.

4.3.4 Drying Model Implementation

Models used for this application are based on those presented by Steele and Wright (1981), where the drying logic contains three sub-routines based on precipitation, current conditions, and prior conditions. These are classified as recovery, rewetting, and normal drying, respectively. The appropriate sub-routine is determined based rainfall or rewetting during the previous time interval, and current rainfall or rewetting. Displayed in Figure 28, is a visualization of the logic behind which dry-down equation the applications run through on each interval. The application first looks for any precipitation for the current interval, if it sees precipitation, it will apply Equation (8) and calculate the increase in moisture content for that interval. If no precipitation is seen, but there is an increase in moisture content between the previous interval and the one before it, the application will go into a recovery period where it will dry down twice the speed as normal. If neither of these conditions are met, the application will proceed with the normal dry-down equation shown in Equation (6).
During normal drying, the peanuts dry using the normal drying rate and moisture content differential between the current moisture content and EMC (Equation (6)). For any biological material, given enough time at constant climactic conditions the moisture content of that material will become in equilibrium with those conditions. This is referred to as EMC, and for whole pod peanuts, as discussed, it can be approximated using the Modified Oswin Equation and coefficients from ASABE Standard D245.7 (ASABE, 2021), which is shown in Equation (9). Using the temperature, and relative humidity, EMC at each time interval was calculated and converted to wet basis percentage using Equation (10).
The value for $K$ in Equation (6) for this application is dependent on the user input for drying rate. When predicting and forecasting drying rates for windrowed peanut, the rate at which the biological material dries is dependent on several factors including temperature, wind speed, relative humidity, solar radiation, and several others. Steele and Wright (1981), defined the change in moisture content using ambient air as the differential between the current moisture content and EMC multiplied by a drying rate constant, this is shown in Equation (6). In Yang et al. (2007), the drying rate constant was calculated for each interval by multiplying a constant by the exponential function of another constant divided by the absolute temperature, this is displayed in Equation (7). However, this calculation for drying rate constant was used for thin layer drying models and may not be applicable for drying peanuts in inverted windrows. For this application, values for drying coefficients for ambient air drying of windrowed peanuts are not well studied. The values for $K$ in this application derived from data sets from publications (Pearman and Butler, 1968) and previous experimentation. Exponential models were fit for each of their provided data sets and paired with the EMC from historical weather data, a $K$ coefficient was fit for each hour interval. The values shown in Table 14 for fast, normal, and slow options are the overall upper bound of the 95% confidence interval, mean, and lower bound of the 95% confidence interval respectively and both at ($\alpha=0.05$). These in-field drying rates are similar to those from Martinez-Feria et al. (2019), where the authors used 0.0281 for $K$. 
The recovery routine uses the same model as normal drying but doubles the drying rate. This is needed as for a brief time after rewetting the crop will dry faster for a brief period of time or “recover”. The third subroutine, classified as rewetting from rainfall, approximates increase in moisture content due to precipitation using the experimentally determine relationship based on the intensity of rainfall shown in Equation (8) (Steele and Wright, 1981).

The above implementation is based on whole pod moisture content; however, producers and buying points ultimately are concerned with kernel moisture content. For example, the target storage moisture content for peanuts is 10% w.b. and any drying fees are charged based upon that moisture content. To address this, the final output was converted to kernel moisture content using the relationship shown in Equation (6).

### 4.4 Example Forecast Outputs

Once all the required inputs are sufficient and the user clicks the generate forecast icon, the application displays a line chart that shows the temperature in Fahrenheit, kernel moisture content, and EMC, where both moisture contents are in percentage wet basis. The application also populates a table with an hour-by-hour summary with date, time, temperature in Fahrenheit, and kernel moisture content in percentage wet basis. An
example forecast including the previously mentioned line chart and table is shown in Figure 29 and Figure 30. Based upon the output in these figures and recommendations from Ogejo (2009), the crop will reach a harvestable moisture content of about 20%\textsubscript{w.b.} after about 4 days. The information populated in the chart and table can be used by a producer to schedule peanut digging and combining operations more effectively, as they can predict when the crop will reach a moisture content that is conducive for combining operations. This improvement of scheduling allows the producer to maximize the time spent in the field and plan the machinery needed accordingly and minimize drying costs from harvesting high moisture peanuts.
Figure 29. Example forecast chart.
As mentioned, the user also has the option to add in temperature and moisture content warnings in the chart and table. These options can be used to warn the user of temperature at or slightly above freezing corresponding with high peanut moisture contents to prevent cold weather injury to peanuts in the field. According to Clemson University Cooperative Extension Services, low temperatures forecasted at 38°F and above digging operations can continue as normal. However, for low temperatures forecasted at 34°F and below to cease digging operations. For any temperature in between is a judgment call on the part of the producer based on expected moisture content, field history, and location

![Figure 30. Example forecast table.](image-url)
(Anco, 2021). An example of use for these warning and highlighting tools is shown in Figure 31 and Figure 32, where the highlighted temperature and moisture content is 34°F and 14% moisture content, wet basis. When a producer reads this plot for an actual cold weather injury scenario, whether they are planning digging operations for a certain day they will either cease current operations to prevent injury or they will postpone operations and wait for warmer weather. Another scenario this functionality may be used is for previously dug peanuts, where they will see impending conditions for injury in the future, they may start combining operations at a higher moisture content to prevent losses due to injury.
Figure 31. Example forecast chart with highlighting rules active.
Figure 32. Example forecast table with highlighting rules active.

4.5 Limitations

The cold weather injury warning rules in the tool are set to the user’s discretion however, there are default settings for the application and documentation is provided from Extension recommendations to guide them in choosing these settings. As discussed in the introduction, early season products will have a lower incoming moisture content and those harvested in later season will have a higher incoming moisture content, making them more susceptible to cold weather injury. These moisture contents can range throughout the year
between 10% and 20%, with an average of around 16%, from the data presented in the introduction.

The tool heavily relies on an accurate starting moisture content to provide timely and accurate results and forecasting, and the user is provided several different dry-down rates which can vary the final moisture content at different points. These EMC models were empirically derived from testing and research from the mid-to-late 20th century, and these models can perform poorly at extreme values of temperature and relative humidity. These poor readings at extreme climactic measurements can also skew the change in moisture content due to inaccurate EMC predictions.

The accuracy of moisture content forecasting is limited as it was only tested on a few data sets with minimal readings of moisture content between digging and combining operations. The tool was tested for accuracy with published datasets from journal articles, conference proceedings, and data from previous tests; and drying rate constants were derived to establish a best fit for these datasets. However, some of these data sets only included a moisture content at digging and combining, and some included one to two readings between digging and combining. The forecasts provided in the web application do not consider solar radiation, soil moisture content, and wind speed when forecasting moisture content while windrowed in the field. High solar radiation and wind speed can increase the rate at which the product dries in the field, and this tool does not account for those factors.
4.6 Conclusions

The Peanut Windrow Drying Calculator was developed to aid peanut producers nationwide with planning and scheduling peanut digging and harvesting operations. Utilizing this application, a producer can utilize site-specific weather forecasts to predict the drying of windrowed and inverted peanuts and schedule combining operations. Producers can also visualize potential windows where cold weather injury can occur, which will help prevent economic losses from unmarketable or devalued peanuts. Improvements to this web application are also planned, although functionality of the model logic has been verified, further research is needed to better define the model inputs (e.g., dry-down coefficients, rewetting rate, and as-dug moisture content). The weather data provided from the API service used in the application also populates data for wind speed and solar intensity which can be implemented in the application during future development. This application is a free service to South Carolina producers, provided by the Clemson University Cooperative Extension Service through the Clemson University Center for Agricultural Technology.
CHAPTER 5. CONCLUSIONS

This thesis evaluated multiple issues related to peanut digging and harvesting, including, factors that contribute to peanut digging losses and developing a web-based decision support tool to forecast windrowed peanut drying. An investigation into the influence of operator experience on mean absolute guidance line deviation showed less experienced operators had larger absolute mean deviations from the row center, compared to highly experienced operators and automatic steering. No differences yield loss were observed between experience groups, but yield loss was also shown to increase with centerline deviation by approximately 95.6 kg ha$^{-1}$ per cm of mean absolute deviation. If a peanut producer were to hire a lower-skilled and lower-cost worker with automatic guidance to run a normally high-skilled task such as peanut digging and can have them perform at the same level or better compared to a high-skilled high-cost operator with manual steering. Combined with estimates of the value of additional yield recovery from using autosteering from this and other studies, investment in a $25,000 automatic guidance system would payoff after digging between 96 to 128 ha of peanuts.

Experiments evaluating the impact of wheel traffic compaction represented an initial investigation into the potential impact of not removing the tractor dual rear wheels prior to digging peanuts. This study did not show any significant changes in yield; however, the windrow volume and final moisture content were both significantly impacted by wheel traffic in the light soil texture. The study also explored the potential of UAS imagery and Digital Surface Models (DSMs) for making informed production decisions by estimating
windrow volume. The approach showed promise for larger windrow volumes, and accuracy could be approved with more involved processing methods.

The development of the peanut windrow drying calculator represents a step forward in providing producers with actionable, site-specific information. This tool helps producers in planning and scheduling their peanut harvesting operations by forecasting changes in moisture and identifying potential risks. With this information, producers can strategically allow additional field drying and save money on drying discounts at buying points. This model was based on limited data from previously published works and though a starting point would benefit from additional research into drying rates and as-dug moisture content.
CHAPTER 6. REFERENCES


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CHAPTER 7. APPENDICES

Appendix A- IRB Exempt Determination

The Office of Research Compliance determined that the proposed activities involving human participants meet the criteria for IRB Level I under 45 CFR 46.101(b). The exempt determination is granted for the enrollment period indicated below.

Principal Investigator (PI) Responsibilities: The PI assumes the responsibilities for the presence of human research as outlined in the Principal Investigator Responsibilities guidelines.

Non-Compliance: If non-compliance is noted, the study may not be continued until an explanation is provided.

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Appendix B- Operator Experience Survey with Informed Consent
Peanut Digging/Equipment Operator Evaluation

Q1
Information about the Research Study
Clemson University

IMPACT OF AUTOSTEER AND OPERATOR EXPERIENCE ON CENTERLINE DEVIATION AND PEANUT DIGGING LOSSES

KEY INFORMATION ABOUT THE RESEARCH STUDY

Study Purpose: The purpose of this research is to evaluate the benefit of precision agriculture technologies to operators with different levels of experience. Specifically, we will examine centerline deviation during agricultural operations and corresponding peanut harvest losses. Participants will perform normal agricultural operations (i.e., peanut digging), while the location of the machine is tracked. You will also complete a short survey to gauge your agricultural equipment operation experience.

Voluntary Consent: Participation is voluntary, and you have the option to not participate.

Activities and Procedures: Your part in the study will be to perform operations including peanut digging, tillage, planting, or mowing. The only difference from your normal activities is that you will be assigned specific sections of the field. You will also complete a short survey to gauge your previous experience operating agricultural equipment.

Equipment that will be utilized in this study could include row crop and utility tractors, peanut digger/inverters, plows, planters, and mowers.

Participation Time: Your participation will occur during normal harvest operations, and specific time dedicated to this study will be approximately 30 minutes, plus an additional 10 minutes to complete the survey.

Risks and Discomforts: There are no foreseeable risks involved in participating in this study other than those encountered in day-to-day life. Data from this project are unlikely to pose a risk for disclosure; however, to further protect participants, data will be made anonymous before long-term storage or publication.

Possible Benefits: You will receive no direct benefits from participating in this research study. However, your responses may help us learn more about the effect that operator experience has
on centerline deviation and peanut digging losses. This will allow for the full benefit of precision technologies to be evaluated. We will also disseminate the results of this study through publications.

EQUIPMENT AND DEVICES THAT WILL BE USED IN RESEARCH STUDY

Equipment that will be used in the study:
Row crop and utility tractors will also be used to pull and power agricultural implements including peanut digger/inverters, plows, planters, or mowers. Participating in this study poses no foreseeable additional safety risks in operating these pieces of machinery. GPS receivers and integrated machine data will be used to monitor centerline deviation that corresponds to your assigned field locations. This will be recorded using either on-board or stand-alone GPS receivers. Additionally, machine task data (digger depth, yield data, engine load, etc.) will also be collected. This data will be paired with corresponding yield or loss data after combining, and is already being collected. Additionally, a tablet or other mobile device will be provided for you to complete the survey.

PROTECTION OF PRIVACY AND CONFIDENTIALITY
The results of this study may be published in scientific journals, professional publications, or educational presentations. We will do everything we can to protect your privacy and confidentiality. We will not tell anybody outside of the research team that you were in this study or what information we collected about you in particular. Data from this project are unlikely to pose a risk for disclosure; however, to further protect participants, any potential identifiers will be removed from the data before long-term storage or publication. The information collected during the study could be used for future research studies or distributed to another investigator for future research studies without additional informed consent from the participants or legally authorized representative. No identifiable information will be collected during the study or on the research study instruments.

CONTACT INFORMATION
If you have any questions or concerns about your rights in this research study, please contact the Clemson University Office of Research Compliance (ORC) at 864-656-6636 or irb@clemson.edu. The Clemson IRB will not be able to answer some study-specific questions. However, you may contact the Clemson IRB if the research staff cannot be reached or if you wish to speak with someone other than the research staff.
If you have any study related questions or if any problems arise, please contact Dr. Aaron Turner at Clemson University at 864-656-9869 or apturne@clemson.edu.

Electronic Consent:
Please select your choice below. Clicking on the "Agree" button indicates that:
- You have read the above information
· You voluntarily agree to participate
· You are 18 years of age or older

   ○ Agree  (1)
   ○ Disagree  (2)

Q20 Please enter your assigned operator number here:

                                                                                           
                                                                                           
Page Break
Q21 Which of the following best describes your experience conducting field operations with agricultural machinery?

<table>
<thead>
<tr>
<th>Activity</th>
<th>No previous experience (1)</th>
<th>I've conducted these operations on a few occasions, but not regularly (2)</th>
<th>I conduct these operations semi-regularly or as a hobby (3)</th>
<th>I conduct these operations professionally (4)</th>
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</thead>
<tbody>
<tr>
<td>General operation (loader work, mowing, etc.) (1)</td>
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<tr>
<td>Row crop operations (planting, harvesting, chemical application) (2)</td>
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<tr>
<td>Peanut digging and harvesting (3)</td>
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</tbody>
</table>

Q3 How many years of experience do you have in operating tractors?

- ○ I have never operated a tractor before (10)
- ○ less than 3 years (11)
- ○ 3-9 years (12)
- ○ 9+ years (13)
Q10 How long has it been since you last operated a tractor?

- Within the last week (4)
- Within the last month (7)
- Within the last year (8)
- A year or more (9)

Q24 What size tractor do you normally operate?

- Compact (25-50 hp) (1)
- Utility (56-100 hp) (2)
- Large Utility/Small Row Crop (100-200 hp) (3)
- Large Row Crop (200+ hp) (4)

Q23 If you were hired as an agricultural equipment operator, what would you charge per hour? (answer in dollars per hour)

For reference: The minimum wage in the State of South Carolina is $7.25/hour, the national average in 2020 for an agricultural equipment operator was $15.38/hour, and the national average in 2020 for a farm manager was $26.68/hour.


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<th>12</th>
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<th>22</th>
<th>28</th>
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<th>36</th>
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<th>50</th>
</tr>
</thead>
<tbody>
<tr>
<td>General operation (loader work, moving, etc.)</td>
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<td>Peanut digging and harvesting</td>
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</tbody>
</table>
Q13 Rate your prior experience digging peanuts.

- I have no peanut digging experience (1)
- I have dug peanuts 1 season or less (2)
- I have dug peanuts for 1-2 seasons (3)
- I have dug peanuts for 2-3 seasons (4)
- I have dug peanuts for more than 3 seasons (5)

Q15 Over the last two years, on average, how many hours per year do you spend digging peanuts? (From 0 to 200+)

Average number of hours spent (0-200+)

Q17 What size digger do you typically operate? (Enter your response in # of rows)

- 2 (21)
- 4 (22)
- 8 (23)
- 8 (24)
Q18 Rate yourself on how you feel your operation (straightness, minimized losses, etc.) of the digger compared your peers and autosteer

<table>
<thead>
<tr>
<th></th>
<th>Considerably Worse (1)</th>
<th>Worse (2)</th>
<th>Better (3)</th>
<th>Considerably Better (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Your Peers (1)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Autosteer (2)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Q19 Have you used any type of machinery guidance before?

☐ Yes (1)

☐ No (2)

Q23 Rate how often you use each technology as a percentage of the total time you spend operating field equipment (Answer in the percentage of time you use each of these technologies)

_____ Manual Steering without markers (1)
_____ Manual steering with markers (2)
_____ Light bar (3)
_____ Autosteer (4)

End of Block: Agricultural Equipment Operation Experience Evaluation
## Appendix C - Experience Survey Results Tables

### Table 15. Mean Desired Wages by Skill Level for Agricultural Operations

<table>
<thead>
<tr>
<th>Experience Level</th>
<th>Mean Wage, General ag operations ($/hr⁻¹)</th>
<th>Mean Wage, Row crop operations ($/hr⁻¹)</th>
<th>Mean Wage, Peanut digging and harvesting ($/hr⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>19.08</td>
<td>20.94</td>
<td>21.48</td>
</tr>
<tr>
<td>Low</td>
<td>19.57</td>
<td>21.59</td>
<td>22.82</td>
</tr>
</tbody>
</table>

### Table 16. Mean Responses for Percentage of Time Different Types of Machinery Guidance Technologies Used by Experience Level

<table>
<thead>
<tr>
<th>Experience Level</th>
<th>Manual guidance, no row markers (%)</th>
<th>Manual guidance with row markers (%)</th>
<th>Lightbar (%)</th>
<th>Autosteer (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>22.8</td>
<td>10.2</td>
<td>5.7</td>
<td>61.3</td>
</tr>
<tr>
<td>Low</td>
<td>78.4</td>
<td>6.9</td>
<td>4.6</td>
<td>10.1</td>
</tr>
</tbody>
</table>

### Table 17. Peanut Digger Size Typically Operated by Participants*

<table>
<thead>
<tr>
<th>Size</th>
<th>2-Row</th>
<th>4-Row</th>
<th>6-Row</th>
<th>8-Row</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>3</td>
<td>4</td>
<td>3</td>
<td>0</td>
</tr>
</tbody>
</table>

*This question was only given to individuals with previous peanut harvesting experience*
Appendix D - Comparison of ArcGIS Pro Near (Geodesic) Function and Haversine Cross-track Distance Equation
Appendix E - K Coefficient Fitting

Figure 33. Exponential models fit for each windrow to predict kernel moisture content for each hour after digging

Figure 34. Distribution for K coefficients calculated