Effect of Nitrogen Rates, Planting Dates, and Irrigation Regimes on Potato Production in the Eastern Shore of Virginia

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Thesis submitted to the faculty of the Virginia Polytechnic Institute and State University in partial fulfillment of the requirements for the degree of

Master of Life Sciences

In

Horticulture

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November 20, 2023

Painter, VA

Keywords: wireworms, multispectral imaging, vegetation index, photogrammetry, fertilization time, soil water dynamic, volumetric water content, growing degree days, subsoil irrigation, soil water sensor.

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ACADEMIC ABSTRACT

Potatoes in the Eastern Shore of Virginia are traditionally planted between late February and early April and harvested between early June and late August. Potato prices are usually higher early into the harvest season and decrease slowly as the season progresses. Early planting dates are desirable for farmers, as it allows them to perceive higher prices for their product, but early planting is also associated with lower air temperature during the early season, which in turn can affect plant development, water and nutrient uptake, and overall yield. Additionally, variations in soil properties often affect nutrient and water availability for plants, as well as the distribution of soil-borne insect pests. Additionally, several techniques are available to map the variations of soil properties in commercial potato fields, but little effort has been made to relate this information to the potential presence of soil-borne pests. Hence, the objective of this project was to evaluate the effect of planting dates, nitrogen (N) rates, and irrigation regimes on potato production. Two comprehensive studies were conducted between February and July 2022 and 2023. The objective of the first study was to evaluate the effect of N rates, planting dates, and soil physicochemical properties in potato production and the presence of soil-borne pests. This study was established in a split-plot design with four replications, with planting dates on the main plot and N rates and time of application on the sub-plot. Late March planting resulted in the highest total tuber yield, while early planting produced significantly larger tubers. Early March planting reduced plant development and emergence, probably due to lower air and soil temperatures. There was no interaction between planting dates and N applications. Using N rates higher than 147 kg ha⁻¹ resulted in no significant differences in total tuber yield. Regression analyses showed that the Normalized Differences Red Edge (NDRE) is an excellent predictor of N content in plant tissue and tuber yield. Moreover, Ca and H saturation percentages were linked to wireworm damage levels using classification algorithms. Similarly, K saturation percentage was identified as a potential predictor of nematode presence in this region. A second study was established with the objective of evaluating the effect of N rates and irrigation regimes on potato production. The study was established in a split-plot design with four replications, with the irrigation method on the main plot and total N rate on the subplot. Results from these experiments showed higher growth and tuber yield when combining overhead irrigation with crop evapotranspiration (ETc) estimation. Moreover, there were no significant differences when using N rates higher than 112 kg ha⁻¹. Overall, results from these experiments suggest no changes in current N rate recommendations for this region. Additionally, these results suggest planting in late March and using irrigation regimes based on evapotranspiration with overhead irrigation systems. Future research should focus on adaptive fertilization based on growing degree days and refinement irrigation determination practices.

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GENERAL AUDIENCE ABSTRACT

In the Eastern Shore of Virginia, nearly 4,000 acres are annually dedicated to fresh white potato farming. The established planting window extends from early March to early April, aligned with peak market demands in late April. However, this traditional planting strategy exposes crops to varying temperatures, potentially affecting water and nutrient demands, as well as overall yield. A research project consisting of two studies was conducted with the objective of evaluating the effect of planting dates, nitrogen (N) rates, and irrigation regimes on potato production. The first study was conducted with the aim of optimizing yield and nutrient management by exploring the interplay between planting dates, N rates, and application timing. The second study evaluated overhead and subsurface drip irrigation systems with irrigation regimes determined either by crop evapotranspiration (ETc) or by soil moisture content through soil water sensors (SWS). Results demonstrated that early March planting resulted in delayed emergence and overall growth due to colder temperatures, while late March plantings produced the highest tuber yields. On the irrigation front, overhead irrigation integrated with ETc estimation consistently improved plant health and augmented yield. In addition, the Normalized Differences Red Edge (NDRE) index, obtained from multispectral drone imaging, produced a significant correlation with N content in plant tissue and with total tuber yields for both studies. This suggests its high potential as a yield prediction tool. Overall, results from these studies reinforce current N rate recommendations for Virginia. Furthermore, they not only refine regional potato cultivation practices but also suggest the need for research pivoting around adaptive fertilization based on growing degree days and the potential refinement of irrigation regimens.

ACKNOWLEDGEMENTS

I would like to take this opportunity to express my sincere gratitude to the following individuals who played an invaluable role in the completion of this thesis:

- My advisor, Dr. Emmanuel Torres: I am deeply thankful for your guidance, expertise, and unwavering support throughout this research journey. Your mentorship has been instrumental in shaping my ideas and refining my skills. Thank you for your patience, for always believing in me, and for providing me with all the means to succeed.
- **My committee members:** Lorena López, Mark Reiter, and Andre Biscaia, thank you for your critical feedback, recommendations, and active engagement in this project. Without your expertise and guidance, this body of work would not be possible.
- **My laboratory:** my friend and co-worker Ricardo Gandini, thank you for providing your friendship and unconditional support. Your camaraderie made this journey more enjoyable. To Josué, Riley, and Suam, this work would not have been possible without your dedication to every task at hand when needed. To Robert Cooley, thank you for coordinating our team and for your commitment to the success of our projects.
- The Eastern Shore AREC team: To Andrew Fletcher, James Warren, John Mason, Joseph Haymaker, Helene Doughty, and other members of the ESAREC, I am deeply grateful for all your support with the establishment, maintenance, and data collection of my experiments. Your aid was vital in the success of this work.
- **My family:** your love, encouragement, and belief in me have always been my pillars of strength in every decision I make. Thank you for always being there for me. I am truly blessed to have you in my life.

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1. CHAPTER 1: LITERATURE REVIEW

1.1 Potato production in Virginia

Potatoes (*Solanum tuberosum*) belong to the Solanaceae family and originated from the South American Andes, from which they traversed a vast historical journey to become a significant crop worldwide. Currently, potatoes are the sixth most important agricultural commodity globally in production volume and value (FAO, 2021). The United States, the world's fifth-largest potato producer, had a total production estimated at 19.9 million Mg and harvested across 373,700 hectares in 2022. Furthermore, potatoes emerge as the largest vegetable crop in the United States, with a total sales value of 4.8 billion dollars for the 2022 year (USDA & NASS, 2023). The country accommodates commercial potato production in 30 states, with 25% of the total production catering to the fresh market (National Potato Council, 2022).

Virginia is often recognized for its contribution to potato cultivation in the United States, where the crop serves as a pivotal income source for farmers, playing a significant role in the regional economy. In 2018, VA recorded a production of over 57,800 Mg, yielding a valuation of \$16.5 million (USDA & NASS, 2019). Potato cultivation in VA is primarily centralized in North Hampton and Accomack counties, where fresh white potatoes are the predominant type. Commonly cultivated white potato varieties in this region include the Atlantic, Superior, Yukon Gold, Kennebec, and Envol, each chosen for their adaptability to local conditions and market preferences. Planting strategies involve planting rows spaced about 91 cm apart (3 ft), with an inrow spacing of 23 cm (9 inches), fostering adequate room for plant development. The cultivation timeline typically sees planting between early March and mid-April and harvesting between late June and early August, depending on weather and market price of potatoes, which decline

rapidly thereafter (USDA, 2022). For this reason, early planting is generally preferred by potato farmers in this region. However, early planted potatoes are potentially susceptible to temperatures below 8°C (46°F), which heavily limit potato seed sprout, development, and growth (Benoit et al., 1983; Haverkort & MacKerron, 2012; Virginia Tech, 2019). Optimum temperatures for potato plant growth range from 16 to 28°C (61 to 82°F) (Benoit et al., 1983). Conversely, late planting can introduce higher temperatures to the crop and accumulated precipitation that can modify plant nutrient demands and overall growth. Additionally, high precipitation and temperatures can increase the risks of nutrient loss due to leaching, increase diseases, pest infestations, and plant heat stress that compromise yield, and potentially low sell price (Garcia-Gonzalez et al., 2022; Tang et al., 2018).

1.2 Wireworm damage, control, and prediction

One of the most pressing concerns in potato production is the infestation by wireworms. As larval stages of click beetles belonging to the family Elateridae, wireworms span thousands of species globally, but only a small portion is detrimental to crops (Poggi et al., 2021). In VA, the dominant wireworm genera are *Melanotus*, *Conoderus*, and *Aeolus* (Kuhar et al., 2003). Wireworm genera can be identified by the shape of the rear end (Poggi et al., 2021). In this region, the two most important wireworm species are *Connoderus vespertinus* (tobacco wireworm), *Melanotus communis* (corn wireworm) (Kuhar et al., 2008). Wireworms inflict extensive damage on various plant structures, including potato seed pieces, roots, and tubers (Van Herk et al., 2022). Tuber damage translates to severe market-quality declines. Potato market standards only allow a 6 to 8% threshold for external and internal defects, making wireworm control essential in commercial potato production (USDA, 2011).

Addressing wireworms requires an integrated approach. Crop rotation, particularly incorporating less preferable crops to wireworms, can deter their proliferation in fields. Potatoes are more susceptible to wireworms when planted after cereal crops, sod, or pasture (Van Herk et al., 2022). However, crops preferred by wireworms can be used as trap crops too. The strategic use of trap crops, such as wheat, has been proven effective in luring wireworms for targeted control, especially when planted around main crops (Vernon et al., 2000). Biocontrol measures, employing natural enemies such as parasitic fungi and entomopathogenic nematodes, offers a sustainable approach (Milosavljević et al., 2020). Chemical control using fipronil, imidacloprid, or thiamethoxam applied to the soil is effective in controlling 50 to 90% of wireworms in potatoes and other field crops. (Kuhar & Alvarez, 2008; Poggi et al., 2021). Furthermore, specific cultural practices, like soil tilling, can also mitigate wireworm numbers by exposing them to surface predators and desiccation (Nikoukar & Rashed, 2022). Previous research evaluating timing of injury in potato tubers in VA suggests that planting date may play a role, as most of the tuber damage occurs in mid-June to early July, despite that most wireworms observations have been reported on late May (Kuhar & Alvarez, 2008).

Soil properties play a crucial role in determining wireworm behavior and resulting damage to crops. This is due to their extended larval stage beneath the soil, which often lasts several years before transitioning into adult click beetles (Parker & Howard, 2001). During this stage, wireworms move vertically within the soil in response to changes in temperature, which exposes them to soil physicochemical properties. For instance, Langdon & Abney (2017) found that wireworm damage intensifies under high moisture soil conditions as opposed to drier soils. Furthermore, Jung et al. (2014) found that the interaction of soil temperature, moisture, and texture type could successfully predict wireworm presence in 85% of the cases. Some natural

enemies of wireworms, such as parasitic fungi and entomopathogenic nematodes, display increased effectiveness in soils rich in organic matter compared to sandy terrains (Ensafi et al., 2018). However, comprehensive research linking wireworm potato damage and soil physicochemical properties, especially nitrogen, remains limited. The exploration of soil texture and nutrient maps analysis in correlation to wireworm presence could potentially introduce new improved management strategies for this pest. Nevertheless, the vertical movement of these organisms poses a challenge for accurate presence estimates.

1.3 Nematodes

Nematodes are microscopic roundworms that inhabit various ecosystems, including agricultural soils. In the context of potato cultivation, nematodes have both beneficial and harmful significance. Detrimentally, certain species, known as plant-parasitic nematodes (PPN), can affect potato yields, causing damage to roots, decreasing nutrient uptake, and facilitating the entry of other pathogens (Kaczmarek et al., 2019). Management recommendations for PPN in VA consider threshold levels of 10 types of nematodes for several crops, but they do not include threshold levels for potatoes (Mehl, 2018). However, these recommendations do consider cyst nematodes, a type of nematode known to be the most damaging in potato production worldwide (Kaczmarek et al., 2003; Trudgill, 1986).

Conversely, there are also beneficial nematodes, often referred to as entomopathogenic nematodes. They serve as biocontrol agents, preying on pests such as wireworms and offering a sustainable approach to pest management (Kabaluk et al., 2005; Poggi et al., 2021; Stock & Goodrich-Blair, 2008). The efficacy of these nematodes is influenced by their movement through water films around soil particles. Consequently, soil properties, especially those like organic matter that contribute to soil water capacity, have been linked to their effectiveness

(Milosavljević et al., 2020; Villani & Wright, 1990). However, comprehensive research bridging nematode presence and soil properties is yet to be fully explored.

1.4 Nitrogen management

Nitrogen is an essential macronutrient in plant production. As one of the primary nutrients responsible for plant growth, it mediates crucial physiological processes, playing a key role on yield and overall tuber quality of the potato plant (Koch et al., 2020). Application of N are usually carried out through synthetic fertilizers which facilitate its uptake by plants. However, this ease comes with associated environmental challenges involving contamination of water bodies and emission of greenhouse gases (Milroy et al., 2019). For instance, potato production in VA is near sensitive water bodies such as the Chesapeake Bay, which represents an environmental hazard in case of N loss due to leaching (Reiter et al., 2012). Furthermore, with the constant increase in fertilizer prices, improvements in N management could potentially increase profitability of production systems (U.S. Bureau Labor of Statistics & FRED, 2023).

Given the significant environmental and profit implications of improper N management, adopting best practices is not only beneficial for securing high crop yields, and economic sustainability of the system, but also essential for safeguarding the environment. Hochmuth et al (2015) highlighted four key principles for efficient nutrient management: using the right rate, applying at the right time, choosing the right source, and selecting the right place. N rate recommendations can vary greatly depending on cultivar, soil conditions, and the region (Cohan et al., 2018; Kuhar et al., 2021; Milroy et al., 2019; Wang et al., 2020). Current N rate recommendations for white potatoes in VA range from 140 to 168 kg N ha⁻¹, but in practice can go up to 269 kg N ha⁻¹ depending on field production potential and farmers personal experience (Reiter et al., 2009). Moreover, N timing recommendations in this region suggest applying 33%

of the recommended N rate at planting and the remaining 67% at emergence. For higher-yielding environments, N timing recommendations suggest a total of three applications: 33% at planting, 50% at emergence, and 17% at flowering (Reiter et al., 2009). Additionally, regional recommendations suggest late N applications based on whole plant petiole nitrate content when it is lower than 27,500 ppm or 2.75% (Reiter et al., 2009). Furthermore, N source selection will depend on various factors including the production system, availability, and cost. There are four primary forms of N fertilizer: ammonia, nitrate, urea, and organic N (Bucher & Kossmann, 2007). Ammonia, due to its positive charge, binds to the soil and is less prone to leaching. Nitrate, on the other hand, is highly mobile in the soil, making it susceptible to leaching (Jury & Nielsen, 1989). Urea acts as a precursor to ammonia and nitrate in the soil and can be subject to volatilization if not adequately incorporated (Jones et al., 2007), and organic nitrogen is usually considered by farmers as inherent from the soil and not included in the total application rate. The right nutrient placement is also paramount, techniques such as banding place N fertilizers considering the plant effective root zone, which for potatoes is in the first 30 cm of soil, thus mitigating N loss. However, the effectiveness of these N management practices can be influenced by irrigation practices, underscoring the interconnectedness of nutrient and water management in potato production.

1.5 Irrigation in potato production

Irrigation plays a pivotal role in the potato cultivation landscape, not only influencing the yield and health of the crop but also mediating the availability and uptake of N. A harmonious balance in irrigation is imperative in intensive systems, as extremes on either end of the spectrum pose challenges. When excessive water is applied, soil nitrate is driven beyond the potato rooting zone, resulting in not only a decrease in nutrient absorption but also in adverse environmental

effects, potentially leading to root hypoxia (Ahmadi et al., 2011; Iwama, 2008; Marsh, 2019). Moreover, excessive irrigation can create conditions with high humidity, which are known to amplify the activity of fungal and bacterial diseases, as well as wireworms and PPN (Adams & Stevenson, 1990; Djaman et al., 2021; Langdon & Abney, 2017; Milosavljević et al., 2020; Villani & Wright, 1990). Conversely, under-irrigation imposes water stress upon the plants, leading to significant yield reduction (Djaman et al., 2021; Onder et al., 2005). Tuber bulking and ripening stages are the most water stress-sensitive stages in potatoes (Djaman et al., 2021; Karam et al., 2005). Deficit irrigation strategies, which expose crops to water stress at a particular stage, have been found less effective than full irrigation in potatoes (Brocic et al., 2009; Djaman et al., 2021; Fabeiro et al., 2001; Karam et al., 2014; Kirda, 2002).]

Various irrigation methods are employed in potato farming, ranging from surface and subsurface drip systems to furrow and sprinkler systems. The choice between them often depends on the specific needs of the cultivation area, available infrastructure, and investment cost. While the precise amount of water applied is crucial, the choice of irrigation method has been found to have negligible effects on potato yield, provided the irrigation is correctly managed (Da Silva et al., 2018). The overarching goal should be to ensure the precise estimation of crop water needs. Multiple methods, including evapotranspiration (ETc), soil moisture sensors, and multispectral images, serve this purpose. Local ETc estimation is often carried out by weather stations employing well-established equations, such as the Penman-Monteith equation (Allen et al., 1998; Monteith, 1965, 1973; Penman, 1948). Research from other regions such as Nebraska, Italy, and Greece, suggests that maximum yields can be obtained with irrigation regimes based on 65 to 130 % of the reference evapotranspiration (Djaman et al., 2021; Foti et al., 1995; Karafyllidis et al., 1996). In VA, this amount would translate to a daily average

of 4 mm of water during the growing season. Soil moisture sensors work based on diverse principles, including gravimetric, tensiometer, dielectric, and remote sensing methods (Yu et al., 2021). Maintaining soil moisture above 50% of the total available water has been found ideal for healthy potato growth (Djaman et al., 2021; Singh, 1969). Additionally, advanced irrigation applications using multispectral imagery from satellites or drones allow for precise ETc mapping in fields. Current approaches are mostly based on the METRIC energy balance model, which use temperature readings from thermal images (Chandel et al., 2020). However, these estimation models have proven difficult to adopt by farmers. Traditional irrigation practices have been grounded in direct observations and estimations, but technological advancements now offer the promise of more precise, data-driven approaches. Foremost among these, remote sensing emerges as an important tool in revolutionizing the way we manage crops.

1.6 Remote sensing

Remote sensing (RS) is the process of acquiring information about an object from a distance without making direct contact. In recent years, scientific research involving RS in agriculture has seen a significant surge. As a result, RS has proven to be of great use for several agricultural applications, including crop health monitoring, yield prediction, irrigation optimization, and weed detection (Mulla, 2013; Weiss et al., 2020). RS is typically achieved using sensors mounted on various platforms, most commonly satellites and Unmanned Aerial Vehicles (drones) (Weiss et al., 2020). While satellite imagery has been foundational for RS applications, it presents certain limitations, including low spatiotemporal resolution and transitional cloud covers, which can impede detailed agricultural analyses. Drones, in contrast, bypass these constraints with higher spatiotemporal resolutions and the ability to operate below

cloud cover (Chandel et al., 2020; Quiros Vargas et al., 2020; Ranjan et al., 2019; Zhang & Kovacs, 2012).

At its core, RS is the analysis of reflected wavelengths of light, termed reflectance, with the use of sensors. Reflectance is captured across various bands, with visible bands representing colors like blue, green, and red, and spectral bands extending beyond the visible spectrum to include wavelengths such as the red edge, near-infrared, and infrared. Spectral imaging is categorized into multispectral, which captures a select number of broad bands, and hyperspectral, which involves many narrower bands (Adão et al., 2017; Alkhaled et al., 2023). Factors such as leaf pigments, leaf structure, and canopy layers play an essential role in influencing plant reflectance (Alkhaled et al., 2023). To enhance signal of specific physiological characteristics of vegetation in RS, mathematical operations between spectral bands are employed, resulting in what are known as vegetation indices. These indices, such as the well-known Normalized Difference Vegetation Index (NDVI), serve as proxies for plant health, growth, and stress levels.

Traditional methods for monitoring crop health require tissue sample collection for N analysis to correct plant N levels through posterior fertilization (Alkhaled et al., 2023; Inoue et al., 2016; Muñoz-Huerta et al., 2013; Zheng et al., 2018). This process, however, is considered destructive by nature, requires physical interaction, and is time-consuming, especially when monitoring large areas, and pays little attention to potential variability of the cropping field, as samples are often randomly selected. RS offers a compelling alternative, delivering vast amounts of information about crop health in a faster and non-destructive way (Alkhaled et al., 2023). For instance, the Normalized Difference Red Edge (NDRE), has been identified to strongly correlate to N levels in potato plant tissue (Morier et al., 2015). By mapping NDRE in potato fields and similar crops, areas with potentially low N levels could be identified in a timely manner for correction without the need for direct interaction.

1.7 Gaps in the existing literature

The existing literature, while comprehensive in several facets, has left relevant areas within the potato production unexplored, particularly in relation to the state of Virginia. Among the foremost of these gaps is the intricate relationship between planting dates, N management, irrigation regimes, wireworm infestations, nematode presence, and soil properties. In the context of N management, while recommended practices have been well-documented, there is limited research on how N rates and application timings interact with planting dates or various irrigation regimes, which are significant given the unique climatic conditions in Virginia. Furthermore, an in-depth understanding of the dynamics between irrigation methods, crop water requirements, and tuber yield could significantly benefit and optimize potato farming in the region.

1.8 Project statement

In this research project, we seek to improve the traditional potato production system in VA by integrating and optimizing multiple management components. This project investigates how planting dates, nitrogen rates, irrigation regimes, remote sensing technologies, soil physicochemical properties, and pests interact with each other within the potato production landscape in VA. Identifying optimal planting dates and nitrogen rates could potentially increase yields and system profitability for farmers in this region. Additionally, improvements in irrigation practices could minimize contamination of sensible water bodies and contribute to plant health and system profitability. Furthermore, evaluation of the relationship between soil physicochemical properties with the presence of soil-borne pests could potentially identify new

strategies for pest management. Given the importance of evaluating these factors in potato production in this region, we proposed the following objectives:

General Objective

• To determine the most adequate planting date, nitrogen rate, and irrigation regime for potato production in the Eastern Shore of Virginia.

Specific Objectives

- 1. To evaluate the effect of planting dates and N regimens on potato growth and yield.
- To evaluate the relationship among different vegetation indices, N regimens, and plant N tissue concentration.
- 3. To evaluate the relationship between soil physicochemical characteristics with wireworm tuber damage and nematode presence.
- 4. To evaluate the effect of irrigation method, irrigation determination methods, and N rates on potato production.
- 5. To evaluate the relationship among different vegetation indices, N rates, and tissue temperature.

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2. CHAPTER 2: EFFECT OF NITROGEN RATE AND PLANTING DATE ON POTATO PRODUCTION

2.1 Abstract

Each year, approximately 4,000 acres of fresh white potatoes are cultivated on Virginia's Eastern Shore. Traditionally, potatoes are planted between early March and early April, with harvesting occurring between late June and late July for early-type varieties. Early planting is favored by farmers because it aligns with the high potato market prices, ensuring high profitability. However, early planting can also expose plants to lower air and soil temperatures, impacting their development and water and nutrient needs. Conversely, late planting results in higher temperatures and rapid growth, also potentially altering nutrient uptake and increasing pest pressure. Given the range of recommended planting dates and the Chesapeake Bay's vulnerability to nutrient runoff from farming, a study was conducted to assess how planting dates, N rates, and application timing affect potato production on the Eastern Shore of Virginia. The study was established in a split-plot design with four replications, where planting date was the main plot, and N rate and application timing were the subplots. Each experimental plot contained 80 plants arranged in two rows. We planted potatoes in early March, late March, and early April, and assessed N rates at 0, 146, 180, 213, and 247 kg N ha⁻¹, distributed across three application regimens. We collected plant emergence at 30 and 45 days after planting, days to flowering, plant reflectance, leaf greenness, tissue nutrient content, and soil-N levels before planting and 30 days after the second N application. Early March planting resulted in delayed plant emergence due to lower temperatures. On the other hand, late March planting resulted in

the highest tuber yield while April planting exhibited larger tubers. Future research should explore fertilization regimes based on accumulation of growing degree days.

2.2 Introduction

Potatoes are the most important non-grain crop in the world and the most valuable be vegetable crop in the United States (FAO, 2021; USDA & NASS, 2023). Within the potato production landscape of the United States, Virginia is a recognized contributor to the regional economy with a production value of 16.5 million dollars for the 2018 year (USDA & NASS, 2019). Early planting is mostly preferred due to the high early-seasonal prices of potatoes, which peak in April (\$25 per 23 kg bag) and decline rapidly after June (from \$20 in June to \$16 in July and August) (USDA, 2022). However, early planted plants are exposed to temperatures below 8° C, which heavily limit growth (Benoit et al., 1983; Haverkort & MacKerron, 2012; Virginia Tech, 2019). In contrast, late planting introduces lower sell prices, higher temperatures (from 9 °C in March to 17 °C in April and May), and higher accumulated precipitation (100 to 150% more in April and May in comparison to March) that modify plant growth and its nutrient demands. Additionally, higher temperatures and precipitations elevate risks of nutrient loss due to leaching and risks of diseases and pest infestations (Garcia-Gonzalez et al., 2022; Tang et al., 2018).

Nutrient management plays a crucial role in potato production. Among all nutrients, N is an essential macronutrient responsible for plant growth, tuber quality, and tuber yield (Koch et al., 2020). Plants uptake N primarily through the application of synthetic fertilizers, which are associated with environmental risks (Milroy et al., 2019). In the Eastern Shore of Virginia, excess N in soils is prone to leaching, which can contaminate sensitive water bodies in the

proximity (Reiter et al., 2012). Current N rate recommendations for this region range from 140 to 168 kg N ha-1, but can go up to 269 kg N ha-1 depending on field production potential (Reiter et al., 2009). Additionally, N timing recommendations for standard environments suggest applying 33% of the recommended N rate at planting and the remaining 67% at emergence, while higheryielding environments should apply 33% at planting, 50% at emergence, and 17% at flowering (Reiter et al., 2009).

Traditional methods for monitoring crop health require tissue sample collection for N analysis to correct plant N levels through posterior fertilization (Alkhaled et al., 2023; Inoue et al., 2016; Muñoz-Huerta et al., 2013; Zheng et al., 2018). However, this process is timeconsuming when monitoring large areas. Remote sensing (RS) offers a compelling alternative by delivering vast amounts of information about crop health in a faster way with no direct contact (Alkhaled et al., 2023). Vegetation indices, derived from RS, are powerful tools that transform raw spectral data into interpretable metrics indicating plant health and vigor. For instance, by mapping vegetation indices, such as the Normalized Difference Red Edge (NDRE), areas of low N levels in plant tissue can be identified (Morier et al., 2015).

Wireworms (Coleoptera: Elateridae) represent one of the primary pests in potato production globally. Wireworms inflict damage in potato plant structures such as seed pieces, roots, and tubers (Van Herk et al., 2022). This larval stage can last several years beneath the soil before transitioning into adults (Parker & Howard, 2001). During this period, these organisms interact with soil properties, which may play a crucial role in determining their behavior. Evidence suggests that wireworm intensifies under high moisture soil conditions as opposed to drier soil conditions (Langdon & Abney, 2017). Additionally, successful prediction of wireworm presence was achieved using soil temperature, moisture, and texture variables (Jung et al., 2014).

Additionally, PPNs also constitute another significant soil-borne pest of major concern in potato production. These organisms affect potato tuber yield by damaging roots, decreasing nutrient uptake, and facilitating the entry of other pathogens (Kaczmarek et al., 2019). However, there is very limited research linking both wireworm and nematode presence with soil physicochemical properties such as nitrogen.

Considering the potential interactions between planting dates, and N uptake, the economic and environmental implications of a persisting inadequate selection of these variables, as well as the challenge posed by attempting to identify wireworms and PPN hot spots in potato fields, the objectives of this project were: (1) to evaluate the effect of planting dates and N regimens on potato growth and yield, (2) to evaluate the relationship among different vegetation indices, N regimens, and plant N tissue concentration, and (3) to evaluate the relationship between soil physicochemical characteristics with wireworm tuber damage and nematode presence.

2.3 Materials and Methods

2.3.1 Experimental design

A study was conducted at Virginia Tech's Eastern Shore Agricultural Research and Extension Center in Painter, Virginia, between March and July in 2022 and 2023. The experiment was set up in a split-plot design with planting date as the main plot and N regimens as sub-plot factor with four replications. During the 2022 season, experimental plots consisted of 80 plants distributed in four rows of 4.57 m, with a spacing of 22.85 cm between plants and 91 cm between rows. Experimental plots during the 2023 season consisted of 80 plants distributed in two rows of 9.14 m, with a spacing of 22.85 cm between plants and 91 cm between rows. This

change was performed to facilitate mechanical applications of N. Planting dates were March 9, March 21, and April 4, as a representation of early March, late March, and early April respectively. Nitrogen rates evaluated were 0, 147, 180, 213, and 247 kg ha⁻¹ distributed in three applications: at planting, at 30, and at 60 days after planting (DAP). We assessed two different distribution proportions for these applications: 50, 30, and 20% of total N rate applied at 0, 30, and 60 DAP respectively, referred as early timing; and 30, 50, and 20% of total N rate, referred as late timing. Late timing was only evaluated for N rates greater or equal to 180 kg ha⁻¹ (Table 2.1).

2.3.2 Crop management

The study site for both years was classified as a Bojac sandy loam soil with a pH of 5.5, an organic matter content of 1.1%, and a nitrate concentration of 17 ppm (Figure 2.1). The selected potato cultivar for the study was Envol, a white, early season, fresh market potato. Before planting, potato seeds were manually cut and treated with Mancozeb (ethylenebisdithiocarbamate) at a rate of 1 kg 100 kg⁻¹ of cut seed. In 2022, potato seed pieces were manually planted, whereas in the 2023, seed pieces were mechanically planted while receiving applications of Ridomil Gold SL (mefenoxam, 420 g ha⁻¹) and Quadris (azoxystrobin, 420 g ha⁻¹). This change was performed to simulate traditional practices in the Eastern Shore of VA. In addition, potato seed pieces in the 2023 received an application at planting of the Belay (clothianidin, 840 g ha⁻¹), except for first planting date (Early March) due to planter malfunction.

Throughout their growth cycle, potato plants in both years were hilled, vine-killed, and harvested at 30, 100, and 110 DAP, respectively. Vine-killing was accomplished using the herbicide Reglone (diquat dibromide, 2.8 L ha⁻¹). In 2022, fertilization was carried out through manual applications of fertilizers triple 10 (10 % N, 10% P, and 10% K), urea, and potash.

Conversely, fertilization in 2023 was carried out through mechanized base applications of liquid Urea containing 30% N, supplemented by manual applications of granular Urea. This change was performed to facilitate fertilization, as manual applications were more time-consuming in 2022. In addition, to fulfill phosphorus (P) and potassium (K) requirements, triple superphosphate and potash were applied at rates of 56 and 112 kg ha⁻¹, respectively. The total rate for P and K fertilizers was fully applied at the time of planting (Table 2.2).

2.3.3 Data collection

Soil nitrate analysis

Soil samples for soil nitrate analysis were collected both before planting and at 4 weeks after planting (WAP), prior to the second N application at 30 days after planting (DAP) for each planting date. Sampling was conducted using a soil probe inserted into the first 30 cm of soil at the center of each planted row. This process was repeated two to three times per plot in three replications, and the resulting sub-samples were combined to create a composite sample per plot. Resulting samples were stored for 4 to 5 weeks in plastic Ziplock bags before being sent to a third-party soil laboratory for analysis (AgroLab).

Plant emergence and flowering

Plant emergence was recorded at 30 and 45 DAP for each planting date. In addition, the days to first flower and days to reach 50% flowering were estimated by regularly inspecting the plots every two to three days after reaching 40 DAP. All plants for all experimental plots were considered during the collection of these variables.

Plant biomass and tissue sampling

Plant biomass samples were collected biweekly from 6 to 12 WAP by collecting two plants from each plot. Samples were stored in paper bags and dried in a hot air dryer at 65°C for

three weeks. Subsequently, the foliar and root biomass components were separately weighed and reported. In 2023, plant tissue samples for N analysis were collected at 6, 8, and 12 WAP. Samples consisted of three to five randomly selected adult leaves from each plot, were also dried in a hot air dryer at 65°C for three weeks before analysis.

Weather data

To assess the growing conditions for each planting date, the number of growing degree days (GDD) was calculated using the following formula:

$$GDD = \frac{(T_{max,30} + T_{min})}{2} - T_{base}$$

Where, $T_{max,30}$ represents the daily maximum air temperature, capped at 30 °C, T_{min} denotes the daily minimum air temperature, and T_{base} is the base temperature equal to 8 °C (Bureau of Reclamation, 2016). Air temperature, precipitation, and evapotranspiration (ET) were measured using a DAVIS Vantage Pro 2 weather station positioned approximately 400 meters from the study site. ET data was used to estimate the irrigation amount based on the accumulation of 100% of the daily ET. Plant irrigation was carried out using a boom irrigation system.

Aerial image acquisition and processing

Biweekly aerial images were captured in 2023, from 4 to 14 weeks after planting (WAP) using a DJI Mavic 3M Enterprise drone. The drone captured RGB bands and four multispectral bands: 560 ± 16 nm green (G), 650 ± 16 nm red (R), 730 ± 16 nm red edge (RE), and 860 ± 26 nm near-infrared (NIR). These images were collected at an altitude of 46 meters above ground level to achieve a ground sampling distance (GSD) of approximately 2.3 cm per pixel when orthorectified.

The collected RGB and multispectral images underwent a series of processing steps. Pix4D Fields software was utilized for 2D reconstruction and orthorectification of images. Multispectral images were radiometrically calibrated using the drone's integrated sun irradiance sensor. Subsequently, orthorectified RGB and reflectance maps were aligned using QGIS software. Resulting maps were then merged, processed, and analyzed using the Python programming language. Processing steps included Minmax normalization of RGB bands, data extraction per plot, removal of soil values across all bands using binary masks, and computation of various multispectral indices as outlined in Table 2.3. Furthermore, the calculation of the area per plant per plot was performed by dividing the area of pixels corresponding to plants by the count of plants present at the time of image capture. This calculation considered the GSD and accounted for plants that were removed during biomass measurements.

Tuber yield and wireworm damage estimation

Tuber yield was assessed by classifying tubers within predefined size groups according to USDA standards and measuring both the total number and weight of tubers in each category for every experimental plot. Tubers were categorized mechanically within four size groups according to diameter: A3 (greater than 8 cm), A2 (7 to 8 cm), A1 (5.5 to 6.99 cm), and B (4.5 to 5.49 cm). Tubers were then manually counted and then weighed using a scale with a precision of 0.02 kg. The resulting data was reported in multiple dimensions, including yield per plant, yield per plot, and yield per hectare. Following the tuber yield measurements, the extent of wireworm damage in tubers was estimated in terms of percentage of tubers affected by wireworms. This assessment was performed with the visual inspection of samples consisting of 10 to 20 tubers from each experimental plot in three replications for the 2023 year, and all tubers in all experimental plots for the 2022 year.

Wireworm and nematode sampling beyond experimental plots

In addition to assessing wireworm damage within the experimental plots, a broader investigation was carried out in seven farms located in the Accomack, North Hampton, and Richmond counties in 2022 and 2023. Three randomly selected sampling points were selected per farm, from which 3 meters of killed vines (~10 plants) were manually harvested. Harvested tubers were counted, weighed, and individually inspected for wireworm damage. Simultaneously, soil samples for soil physicochemical analysis and nematode presence were collected in each sampling point. Soil properties evaluated are listed in Table 2.4. Each soil sample consisted of a combination of two to three subsamples collected using a soil probe inserted in the first 30 cm of soil at the center of planted rows. Soil samples for nematode analysis were carefully stored below 7 °C for no more than 5 days before analysis. Analysis consisted in counting 11 types of nematodes per 500 cc of soil, as listed in Table 2.5. Results were reported as the total count of nematodes per 500 cc of soil per type of nematode.

2.3.4 Data analysis

The collected data, including soil nitrate at 30 DAP, tuber yield data, and various other variables, were analyzed using R and Python programming languages within the Visual Studio Code software environment. For soil nitrate levels at 30 DAP and tuber yield data, analysis of variance (ANOVA) was employed to explore the impact of different factors on these variables. Wherever the ANOVA tests revealed significant effects of factors, post hoc analyses were conducted using Fisher's least significant difference (LSD) at a 5% level of significance to distinguish means.

Pearson's correlation analyses were carried out to identify potential predictors for various variables, including dry biomass, N percentage in plant tissue, total yield, and wireworm injury

percentage. Subsequently, regression analyses were performed using the variables that exhibited the highest correlations for each target variable. Additional regression analyses were conducted for vegetation indices and area per plant variables, using the accumulation of GDD as a predictor variable.

To assess which soil physicochemical properties could potentially predict wireworm injury levels and nematode presence levels, classification models were developed. Wireworm injury percentage was categorized as either low or high using a threshold of 15%. This threshold was determined based on the distribution of injury percentages in collected samples. Notably in Figure 2.2. 2022 and 2023 wireworm damage percentage data distribution based on insecticide application from sampled farms located in North Hampton and Accomack counties, Virginia., the 75th percentile of injury percentages in samples with insecticide and the minimum injury percentage in samples without insecticide both aligned with this 15% threshold. For nematode presence, presence level was classified as high if the total sum of individual nematode counts exceeded 100 nematodes per 500 cc of soil. This threshold represents the median value of the thresholds listed in Table 2.5. Two classification models were constructed for each variable using decision tree and random forest algorithms. The data was divided into training (80%) and test (20%) sets for model development and evaluation. The evaluation of model performance on datasets encompassed five key metrics: precision, recall, F1 score, accuracy, and the area under the receiver operating characteristic curve (AUC). Furthermore, the importance of variables used by each model was reported in descending order of significance as determined by the model.

2.4 Results and Discussion

2.4.1 Observations for the 2022 season

In 2022, there were no significant differences between treatments for the measured variables. This was due to multiple fertilization and disease management challenges that arose. These challenges severely impacted data collection and data quality for this year. Particularly, manual fertilization in combination with the planting setup (four rows per plot) required more time for fertilizer preparation than most of the other activities combined, thus limiting the timely and proper execution of other tasks. In addition, several mistakes were made in the distribution of N throughout plant development during the 2022 season, in which application of N at planting was 70% lower than planned. Although this error was corrected in the second N application, it may have contributed to the minimal visual differences and reduced plant growth. Furthermore, manually planting seed pieces resulted in seeds not being deep enough, which exposed seed pieces to air temperatures. This may have also contributed to the reduced plant growth. Additionally, potato plants experienced a disease mid-season that could not be identified, which resulted in early senescence of plants.

Given that most of the problems in the 2022 season were due to the manual execution of activities, planting setup and fertilization in the 2023 season was modified for mechanical execution. Nevertheless, because treatment protocol was not correctly followed during 2022 and due to the multiple potential repercussions of the errors committed, we determined that the inclusion of 2022 data would only introduce noise into our results. For this reason, and to ensure correct statistical comparisons and conclusions, data from the 2022 year was excluded. Only the wireworm injury data and nematode analyses from the 2022 year were exclusively utilized in the classification algorithms evaluated.

2.4.2 Plant emergence at 30 and 45 days after planting

In 2023, there was no interaction among planting dates, N rates, and N time of application for potato emergence at 30 and 45 days after planting. However, the was an individual factor effect of planting date. Late March planting resulted in 14% higher plant emergence than Early April and 71% higher emergence than Early March at 30 days after planting. Furthermore, at 45 days after planting, there was no difference in plant emergence among all evaluated planting dates (Table 2.6). There was no effect of N rates on plant emergence at 30 and 45 days with averages of 44.8 and 72.5 plants emerged, respectively (Table 2.6). Similarly, there was no effect of time of application on with an average of 44.8 plants at 30 days, and 72.6 at 45 days (Table 2.6). An average of all N treatments in Late March planting was also compared to the control with no N applied and the relative control with equal distribution of N applied. Data resulted in no significant difference among treatments with an average of 72.1 plants emerged at 30 days, and 72.7 at 45 days (Table 2.7). The percentage of emergence could not be determined as the exact number of seeds planted in each plot was not counted. Although planting setup estimated 80 plants per plot, seed size variability likely resulted in non-uniform planting, resulting in a variable number of plants per plot.

2.4.3 Growing degree days and plant physiological events

During the 2023 season, temperatures rose steadily from late March until early July, as illustrated in Figure 2.3. This trend was reflected in the accumulation of growing degree days (GDD) for each planting date, with early April planting accumulating more GDD than the rest of the planting date treatments (Figure 2.4). The average daily rate of GDD accumulation for the early April planting was 9% higher than late March planting and 21% higher than early March planting (Table 2.8). A distinctive observation is the occurrence of physiological events at

certain GDD ranges. Emergence took place between 180 to 210 GDD, the first flowering between 250 to 300 GDD, and 50% flowering was observed between 350 to 400 GDD. This synchronization in the occurrence of physiological events based on the accumulation of GDD can have direct implications for the study's N application regimen. Particularly, although the timing of N applications was consistent in terms of days after planting (DAP), it was different in terms of physiological stage for each planting date. Specifically, at the time of the second N application, Early March planted potatoes had still not emerged, compared to later planting dates that had emerged. Moreover, during the third N application, Early March planted plants were starting to flower, whereas later planting dates had passed 50% flowering (Figure 2.4).

2.4.4 Precipitation and soil nitrate levels

During the 2023 season, several heavy precipitations events (>25 mm) were observed, notably at the end of the season (Figure 2.3). This distribution in precipitation led to the early April planting date experiencing significantly higher rainfall than the rest of planting dates (Figure 2.5). Heavy rainfalls have been linked with potential nitrate leaching from the potato plant's root zone by several authors (Ahmadi et al., 2011; Iwama, 2008; Jury & Nielsen, 1989; Marsh, 2019; Reiter et al., 2012). However, ANOVA test for soil nitrate level at 30 DAP did not result in any significant differences between the planting dates nor the interaction between planting dates and nitrogen rates. Nevertheless, there were significant differences between varying N rates, especially when compared with the control treatment without N applied (Table 2.9).

2.4.5 Plant area estimations

Analysis of the collected aerial imaging provided significant insights into plant growth variations between planting dates. Visually, differences in the green-covered area, indicative of

plant growth, were evident across planting dates (Figure 2.6). The points of plant emergence and when plants started to reduce their foliar biomass (due to senescence) differed based on weeks after planting (WAP) depending on the planting date. While biomass measurements were collected during this period, most of the samples were damaged and lost due to malfunctioning of the dryers. The remaining samples were insufficient for statistical comparisons. However, they were used in the identification of potential predictors of plant biomass. A correlation analysis using Pearson's coefficient identified plant area estimated from aerial imaging as highly correlated to above ground biomass (Figure 2.7). This strong relationship was further explained in a regression analysis, which resulted in an exponential equation with a coefficient of determination (\mathbb{R}^2) of 0.75 (Figure 2.8).

When observing plant area growth curves based on WAP, there were significant differences between planting dates (Figure 2.9). The curve for early April planting was steeper and higher than curves for earlier planting dates, indicating a higher rate of growth than other planting dates. On average, early April planting resulted in a rate of growth 14% higher than late March planting and 64% higher than early March planting. This suggests that plants may have benefitted from warmer temperatures and higher accumulation of GDD. Furthermore, plant area accumulation curves began to converge when evaluated against GDD accumulation (Figure 2.10). The relationship between plant area growth and GDD accumulation was further detailed by a third-degree polynomial regression, presenting an R² value of 0.78 (Figure 2.11). The peak of this function, at 432 GDD, marks the point at which above ground biomass starts to decrease, signaling plant senescence.

Regarding N application, the absence of N led to a significant reduction in plant area across all planting dates (Figure 2.12). The timing of N application also affected the plant area

distinctly for the early April planting date at both 6 and 8 WAP (Figure 2.13). Early N application timing produced higher values of plant area compared to late application in potatoes planted in early April. This may suggest that late planting dates might benefit from a more frontloaded N application given their early emergence and faster growth rate.

2.4.6 Vegetation indices

Normalized Difference Vegetation Index (NDVI) values for early March and late March planting dates were significantly lower (23% and 14% less respectively) than early April planting date at emergence (Figure 2.14). This suggests that early-planted potatoes exhibited signs of stress during emergence, likely due to the low temperatures during their emergence, low root development, and or low availability of N. Moreover, plants with no N application displayed significantly reduced NDVI values compared to N applied treatments across all planting dates (Figure 2.15). This observation is consistent with findings from Morier et al. (2015), who associated NDVI with plant health indicators such as N content in potato plant tissue. When evaluating NDVI values against accumulated GDD across planting dates, a curve pattern was identified. This relationship was best described by a third-degree polynomial with an R² value of 0.75 (Figure 2.16). The peak of this function, at 352 GDD, suggests a pivotal shift in plant physiology across planting dates, evidenced by the declining NDVI values from this point.

While collected plant tissue samples for N analysis were limited in quantity, preventing statistical comparisons, the data provided significant insights. Correlation analysis using Pearson's coefficient identified Normalized Difference Red Edge (NDRE) as the most significant correlator of nitrate content in plant tissue (0.9). Notably, all other indices also exhibited high correlations (>0.7) (Figure 2.17). Subsequent regression analysis explained the linear relationship between NDRE and nitrate percentage in plant tissue with an R² value of 0.81

(Figure 2.18). This aligns with the results presented by Morier et al.(2015), which identified NDRE as the third highest correlator to plant N content among 30 evaluated hyperspectral indices.

The response of NDRE values mirrored that of previously discussed NDVI curves. NDRE values for early planting dates were significantly lower at the start of the season, indicating reduced nitrate content in plant tissue (Figure 2.19). As anticipated, treatments with no N application exhibited significantly lower NDRE values across planting dates when compared to N applied treatments, resulting 24% lower values on average (Figure 2.20). This further implies that treatments with no N application had diminished N content. In addition, NDRE values were significantly higher for early N timing in April planting compared to late N timing, resulting in 10% higher values on average (Figure 2.21). This might suggest that for later planting dates, a higher proportion of N applied at planting might be beneficial for plant development, which corroborates previous observations on plant area growth.

2.4.7 Tuber yield and quality

The ANOVA test revealed significant differences in tuber yield for N rate and planting date factors. Despite earlier observations on plant health indicators, N application timing had no significant difference in tuber yield. Predictably, the absence of N application resulted in the lowest yield. However, when N was applied, the differences in yield across N rates were not statistically significant (Table 2.10). All treatments with N application met the expected yield range for this region (22.4 to 26.9 Mg ha⁻¹), reinforcing validity of prior N rate recommendations (Reiter et al., 2009). Regression analysis of total yield as a function of N rate suggests that 227 kg of N ha⁻¹ maximizes tuber yield across all planting dates (Figure 2.22). Variables such as total number of tubers, average weight per tuber, and tuber size class proportion mirrored this pattern.

Treatments with N application exhibited substantially higher values than those without, but there was negligible variance among them (Table 2.10 and Figure 2.23). Planting in late March maximized total yield when compared to early March planting but had no difference with early April planting (Table 2.10). Early April planting, however, had significantly higher average weight per tuber in comparison with the other planting dates, 19% higher on average (Table 2.10). This is further evidenced by a larger proportion A-sized class tubers (Figure 2.24). Yield results suggest that the combination of late March planting with 180 kg of N ha⁻¹ is the most adequate recommendation to increase potato tuber yield. Additionally, NDRE values suggest that early N application timing may increase N content in plant tissue, especially in early April planting date. Moreover, this combination of the above mentioned recommendations resulted in the highest estimated gross profit per hectare when compared to traditional practices (Table 2.11) and Table 2.12).

Furthermore, a correlation analysis segmented by planting date using Pearson's coefficient identified total plant area as the highest correlator (>0.87) to tuber yield (Figure 2.25). Each planting date exhibited total plant area as the primary correlator, but this peak correlation was reached at differing WAP. It was observed that these peaks coincided with the WAP that maximized plant area. Considering this, subsequent regression analyses took the maximum plant area as the primary input. The resulting linear relationships for March, April, and the combined planting dates yielded R² values of 0.83, 0.77, and 0.69, respectively (Figure 2.26). Applications of these models could potentially predict tuber yield 4 to 6 weeks before harvest. However, their application in real-world settings mandates additional scrutiny and fine-tuning. The depicted relationships could be specific to the cultivar studied. Moreover, given our methodology's

sensitivity to the presence of extraneous vegetation, like weeds, the actual plant area estimations could be skewed in more complex agricultural settings.

2.4.8 Wireworm damage evaluation and prediction

The ANOVA test for wireworm damage percentage in tubers also showed significant differences for N rate and planting date factors. No application of N resulted in significantly higher wireworm damage compared to using the maximum N rate (247 kg N ha⁻¹). However, treatments without N application did not display any significant difference when compared to other evaluated N rates (Table 2.10). Early March planting had significantly higher wireworm damage than the rest of planting dates, attributed to the absence of insecticide application against wireworms during planting. Conversely, subsequent planting dates exhibited no significant difference in wireworm damage between them (Table 2.10). Wireworm damage levels per planting date were consistent with previous research evaluating the efficacy of several insecticides wireworm control in the Eastern Shore of Virginia (Kuhar & Alvarez, 2008). However, while their findings suggest that larger tubers are more susceptible to wireworm damage, our early April planting, which produced the largest tubers, did not exhibit higher damage levels. A plausible explanation could be rooted in the interplay of evaluating wireworm damage, tuber size class, and planting dates, which was not assessed in this study.

Two correlation analyses using Pearson's coefficient were conducted to identify soil physicochemical properties displaying positive (>0.4) and negative (<-0.4) correlation to wireworm damage in tubers. This was done across tubers sourced from our study and six other farms. Results showed that soil nitrate concentration and hydrogen (H) saturation percentage were positively correlated to wireworm damage (Figure 2.27). Conversely, sodium (Na)

saturation percentage, calcium (Ca) saturation percentage, and soil pH showcased a negative correlation (Figure 2.28).

To predict injury levels (categorized as high or low based on a 15% threshold), all measured soil variables were integrated into two classification algorithms: decision tree and random forest. Their respective AUC scores on training data resulted in 0.80 and 0.88, while on test data was 0.54, and 0.75 (Table 2.13). This indicates a superior fit for the random forest model, making it a more suitable model for this wireworm damage dataset. However, the intricate relationships between the soil properties are more easily explainable using a decision tree model (as depicted in Figure 2.29). In contrast, random forest models are considered "blackbox" models, with internal workings harder to explain (Moeyersoms et al., 2015). Nevertheless, both models prioritized Ca and H saturation percentages in their computations, although in varying orders of importance. In the random forest model, soil nitrate scored highest importance, accounting for 30% of the model (Figure 2.30 and Figure 2.31).

2.4.9 Nematode presence level prediction

Similar to wireworm damage prediction, to predict nematode presence (categorized as high or low based on threshold of 100 nematodes per 500 cc of soil), all the available soil variables were used in a decision tree and random forest algorithms. Their respective AUC scores on training data resulted in 0.88 and 0.73, while on test data was 0.58, and 0.58 (Table 2.14). This indicates a superior fit for the decision tree model, which is further detailed in Figure 2.32. Although the decision tree model performed better than the random forest model in the training dataset, both models had a low performance on the test dataset, making them not suitable for un-seen data or real-world scenarios. However, both models assigned the highest importance score to K saturation percentage. The decision tree model assigned over 60% of

significance to this factor (Figure 2.33). Meanwhile, in the random forest model, the K saturation percentage combined with soil pH contributed to 50% of the model's significance (Figure 2.34).

2.5 Conclusion

Late March planting in combination with 180 kg of N ha⁻¹ resulted in the highest tuber yield and gross profit by a margin of 24% and 6%, respectively, when compared to traditional practices with Envol potatoes on the Eastern Shore of Virginia. In addition, early April planting tuber yield resulted in significantly larger tubers compared to other planting dates. N timing did not have a significant effect in tuber yield. However, NDRE and plant growth evaluation for early April planted potatoes suggests that potato plants may benefit from higher proportions of N applied at planting. Regarding pest damage, wireworm damage was higher when no N was applied. Moreover, soil physicochemical properties such as Ca and H saturation percentage and nitrate content were identified as good predictors of wireworm damage level in classification algorithms. Similarly, NDRE was identified as a great predictor of N content in plant tissue, as stated in previous studies. Finally, maximum plant area was identified as a great predictor of tuber yield 4 to 6 weeks before harvest. Future research should explore N applications and aerial measurements in varying levels of accumulation of GDD.

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		Sufficiency Levels			
	Analysis	Deficient	Low	Sufficient	High
pH	5.53				
Buffer pH	6.8	-			
Soluble Salts, EC mmho/cm	0.13			•	
Nitrate-N, ppm N	17.0			- 1	
Nitrate-N, Lbs N/A	41.00				
Depth	0 - 8 in				
Ammonium-N ppm	6.0				
Phosphorus, ppm P	107				
P Saturation	27			• 1	
UMD P FIV	119				
Potassium, ppm K	92			4 1	
Calcium, ppm Ca	404				
Magnesium, ppm Mg	71			• 1	
Sulfur, ppm S	7				
Boron, ppm B	0.60				
Zinc, ppm Zn	0.83		I		
Manganese, ppm Mn pH sensitive	32.0				
Copper, ppm Cu	1.14			- 1	
Sodium, ppm Na	14				
CEC Sum of Cations, meq/100g	3.9				
H % Saturation	25				
K % Saturation	6				
Ca % Saturation	52				
Mg % Saturation	15				
Na % Saturation	2				
Organic Matter, %	1.1				
Organic Matter (LOI @ 455 C), %	1.92				
Est. Organic Carbon, %	0.63				
Aluminum, ppm Al	890.0				
Iron, ppm Fe	180.0				

Figure 2.1. Soil fertility analysis before the establishment of the experiment in March 8, 2023, at the Eastern Shore Agricultural Research and Extension Center in Painter, Virginia.



Figure 2.2. 2022 and 2023 wireworm damage percentage data distribution based on insecticide application from sampled farms located in North Hampton and Accomack counties, Virginia.



Figure 2.3. Daily maximum and minimum temperature and daily precipitation data from late February to early July 2023 at Painter, Virginia.



Figure 2.4. Relationship between growing degree days accumulation and potato physiological events per planting date in 2023 at Painter, Virginia.



Figure 2.5. Accumulated precipitation and potato emergence per planting date in 2023 at Painter, Virginia.



Figure 2.6. Biweekly aerial images of specific potato plots per planting date with soil values removed in 2023 at Painter, Virginia.



Figure 2.7. Correlation matrix heatmap of variables highly correlated (>0.6) with potato foliar, root, and total dry biomass measurements collected in 2023 at Painter, Virginia. Values represent Pearson's coefficient of correlation.



Figure 2.8. Regression for potato dry foliar biomass as a function of plant area measured using aerial images collected in 2023 at Painter, Virginia.



Figure 2.9. Biweekly potato plant area growth curves per planting date from 4 to 14 weeks after planting for 2023 season in Painter, Virginia.



Figure 2.10. Potato plant area growth curves per planting date by accumulation of growing degree days for the 2023 season in Painter, Virginia.



Figure 2.11. Regression for potato plant area measured with aerial images as a function of growing degree days for 2023 season at Painter, Virginia.


Figure 2.12. Potato plant area growth curves per nitrogen rate and planting date in 2023 at Painter, Virginia.



Figure 2.13. Potato plant area growth curves per nitrogen timing and planting date in 2023 at Painter, Virginia.



Figure 2.14. Potato Normalized Difference Vegetation Index (NDVI) by accumulated growing degree days (GDD) per planting date for 2023 season in Painter, Virginia.



Figure 2.15. Effect of planting date and nitrogen rate on potato Normalized Difference Vegetation Index (NDVI) curve in 2023 season at Painter, Virginia.



Figure 2.16. Regression for potato Normalized Difference Vegetation Index (NDVI) values as a function of growing degree days for 2023 season in Painter, Virginia.



tissue_N_pct

Figure 2.17. Correlation matrix heatmap of variables highly correlated (>0.6) with percentage of nitrogen in potato plant tissue between 6 to 12 weeks after transplant for 2023 season in Painter, Virginia. Values represent Pearson's coefficient of correlation.



Figure 2.18. Regression for nitrogen percentage in potato plant tissue as a function of Normalized Difference Red Edge (NDRE) value for 2023 season in Painter, Virginia.



Figure 2.19. Normalized Difference Red Edge (NDRE) by accumulated growing degree days (GDD) per planting date for 2023 season in Painter, Virginia.



Figure 2.20. Effect of planting date and nitrogen rate on potato Normalized Difference Red Edge (NDRE) curve for 2023 season in Painter, Virginia.



Figure 2.21. Effect of planting date and nitrogen application timing on potato Normalized Difference Red Edge (NDRE) curve for 2023 season in Painter, Virginia.



Figure 2.22. Regression for total tuber yield as a function of nitrogen rate for 2023 season in Painter, Virginia.



Figure 2.23. Effect of nitrogen rate in total potato tuber yield per size class for 2023 season in Painter, Virginia.



Figure 2.24. Effect of planting date in total potato tuber yield per size class for 2023 season in Painter, Virginia.



Figure 2.25. Correlation matrix heatmap of highly correlated (>0.6) variables with total tuber yield per planting date for 2023 season in Painter, Virginia. Values represent Pearson's coefficient of correlation.



Figure 2.26. Regression for total potato tuber yield as a function of maximum plant area measured with aerial images collected in 2023 in Painter, Virginia.



Figure 2.27. Correlation matrix of positive correlated (>0.4) variables with potato tuber wireworm injury percentage and injury level for 2023 season in Painter, Virginia. Values represent Pearson's coefficient of correlation.



Figure 2.28. Correlation matrix of negative correlated (<-0.4) variables with potato tuber wireworm injury percentage and injury level for 2023 season in Painter, Virginia. Values represent Pearson's coefficient of correlation.



Figure 2.29. Decision tree classification model for potato tuber wireworm injury level using soil chemical properties measured from samples collected in 2022 and 2023 in North Hampton and Accomack counties, Virginia.



Figure 2.30. Feature importance of the decision tree classification model for potato tuber wireworm injury level for 2022 and 2023 data collected in North Hampton and Accomack counties, Virginia.



Figure 2.31. Feature importance of the random forest classification model for potato tuber wireworm injury level for 2022 and 2023 data collected in North Hampton and Accomack counties, Virginia.



Figure 2.32. Decision tree classification model for nematode presence level using soil chemical properties measured from samples collected in 2022 and 2023 in North Hampton and Accomack counties, Virginia.



Figure 2.33. Feature importance of the decision tree classification model for nematode presence level for 2022 and 2023 data collected in North Hampton and Accomack counties, Virginia.



Figure 2.34. Feature importance of the random forest classification model for nematode presence level for 2022 and 2023 data collected in North Hampton and Accomack counties, Virginia.

Treatment	Dianting data	Nitrogen	Total nitrogen rate	Nitr	ogen applicat	ions
number	Planting date	timing	(kg ha^{-1})	At planting	At 30 DAP	At 60 DAP
1		None	0	0	0	0
2		None	146	56	56	34
3			180	90	57	34
4	Early March	Early	213	123	56	34
5	Earry March		247	157	56	34
6			180	56	81	34
7		Late	213	56	123	34
8			247	56	157	34
9		None	0	0	0	0
10	_	None	146	56	56	34
11		Early	180	90	57	34
12	Lata Marah		213	123	56	34
13	Late March		247	157	56	34
14			180	56	91	34
15		Late	213	56	123	34
16			247	56	157	34
17		None	0	0	0	0
18		None	146	56	56	34
19			180	90	57	34
20	Ecular Annil	Early	213	123	56	34
21	Early April		247	157	56	34
22	-		180	56	91	34
23		Late	213	56	123	34
24			247	56	157	34

Table 2.1. Treatment description of experiment conducted from March to August 2022 and 2023 at Painter, Virginia.

Treatment	Diantin a data	Nitrogen		At planting			30 DAP			60 DAP			Total	
number	Planting date	timing	Ν	P_2O_5	K ₂ O	Ν	P_2O_5	K ₂ O	Ν	P_2O_5	K ₂ O	Ν	P_2O_5	K_2O
1		None	0	56	112	0	0	0	0	0	0	0	56	112
2	_	None	56	56	112	56	0	0	34	0	0	146	56	112
3			90	56	112	57	0	0	34	0	0	180	56	112
4	Forly Moroh	Early	123	56	112	56	0	0	34	0	0	213	56	112
5			157	56	112	56	0	0	34	0	0	247	56	112
6			56	56	112	81	0	0	34	0	0	180	56	112
7		Late	56	56	112	123	0	0	34	0	0	213	56	112
8			56	56	112	157	0	0	34	0	0	247	56	112
9		None	0	56	112	0	0	0	0	0	0	0	56	112
10	_		56	56	112	56	0	0	34	0	0	146	56	112
11			90	56	112	57	0	0	34	0	0	180	56	112
12	Lata Marah	Early	123	56	112	56	0	0	34	0	0	213	56	112
13			157	56	112	56	0	0	34	0	0	247	56	112
14			56	56	112	91	0	0	34	0	0	180	56	112
15		Late	56	56	112	123	0	0	34	0	0	213	56	112
16			56	56	112	157	0	0	34	0	0	247	56	112
17		None	0	56	112	0	0	0	0	0	0	0	56	112
18	_	None	56	56	112	56	0	0	34	0	0	146	56	112
19			90	56	112	57	0	0	34	0	0	180	56	112
20	Early April	Early	123	56	112	56	0	0	34	0	0	213	56	112
21			157	56	112	56	0	0	34	0	0	247	56	112
22			56	56	112	91	0	0	34	0	0	180	56	112
23		Late	56	56	112	123	0	0	34	0	0	213	56	112
24			56	56	112	157	0	0	34	0	0	247	56	112

Table 2.2. Complete fertilization plan per treatment for experiment conducted from March to August 2022 and 2023 at Painter, Virginia.

DAP: days after planting

Index Name	Abbreviation	Formula
Chlorophyll Index Green ^a	CIG	(NIR / G) - 1
Chlorophyll Vegetation Index ^b	CVI	NIR * R / G^2
Green Normalized Difference Vegetation Index ^c	GNDVI	(NIR - G) / (NIR + G)
Normalized Difference Red Edge ^c	NDRE	(NIR - RE) / (NIR + RE)
Normalized Difference Vegetation Index ^d	NDVI	(NIR - R) / (NIR + R)

Table 2.3. List of multispectral indices calculated and their equations.

Bands: green (G), red (R), red edge (RE), and near infrared (NIR) ^a (A. A. Gitelson et al., 2003), ^b (Vincini et al., 2008), ^c (A. Gitelson & Merzlyak, 1994), ^d (Tucker, 1979)

Variable	Unit	Variable	Unit
pН		Manganese	ppm
Buffer pH		Copper	ppm
Soluble salts (EC)	mmho/cm	Boron	ppm
CEC sum of cations	meq/100g	Organic matter	%
Aluminum	ppm	P saturation	%
Nitrate-N	ppm	H saturation	%
Phosphorus	ppm	K saturation	%
Potassium	ppm	Ca saturation	%
Calcium	ppm	Mg saturation	%
Magnesium	ppm	Na saturation	%
Sodium	ppm	Sand	%
Sulfate-S	ppm	Silt	%
Zinc	ppm	Clay	%
Iron	ppm		

Table 2.4. Soil physicochemical properties evaluated in soil analyses.

Extraction method: Mehlich 3

Common name	Scientific name	Threshold (nematodes per 500 cc of soil) ^a
Root-knot	Meloidogyne sp.	50
Cyst	Heterodera sp.	20
Lesion	Pratylenchus sp.	100
Stunt	Tylenchorhyncus sp.	300
Spiral	Helycotylenchus sp.	1000
Lance	Hoplolaimus sp.	300
Ring	Mesocriconema sp.	200
Stubby root	Trichodorus sp.	90
Sting	Belonolaimus sp.	10
Dagger	Xiphinema sp.	100
a T11.1111	$f_{1} = \frac{1}{2} (M_{1} + 1) (M_{2} + 1) + 1) $	

Table 2.5. List of nematodes counted in soil nematode analyses with their threshold level for the 2022 and 2023 year.

^a Threshold levels for soybean (Mehl, 2018)

Easter	Plant er	mergence	
	30 days	45 days	
Planting date (PD)			
Late March	71.66 a	73.66	
Early April	62.70 b	72.58	
Early March	0.00 c	71.75	
Significance	< 0.001	0.3120	
Nitrogen rate (NR)	0.9250	0.8962	
Timing of application (TA)	0.5799	0.2795	
PD x NR	0.9975	0.9611	
PD x TA	0.8469	0.5556	
NR x TA	0.4605	0.4269	
PD x NR x TA	0.7098	0.7162	

Table 2.6. Effect of planting date, nitrogen rate, and timing of application on potato emergence at 30 and 45 days after planting for 2023 season in Painter, Virginia.

Table 2.7. Effect of late March planting date, no nitrogen application, and no variation in timing of nitrogen application on potato emergence at 30 and 45 days after planting for 2023 season in Painter, Virginia.

Factor	Plant emergence			
	30 days	45 days		
Late March	71.66	72.58		
Control (No Nitrogen)	71.00	71.75		
Control (No diff in time of application)	73.75	73.75		
Significance	0.4973	0.6949		

Table 2.8. Average daily growing degree days accumulation per planting date for 2023 season in Painter, Virginia.

Planting date	Average daily GDD accumulation (GDD day ⁻¹)
Early March	7.29
Late March	8.13
Early April	8.83

Factor	Soil Nitrate (ppm) ^a
Nitrogen rate (kg ha ⁻¹) (NR)	
0	22.57 с
146	38.20 b
180	47.39 b
213	72.90 a
247	60.27 ab
Significance	< 0.001
Planting date (PD)	0.0573
PD x NR	0.8615

Table 2.9. Effect of planting date and nitrogen rate on soil nitrate levels at 30 days after planting for 2023 season in Painter, Virginia.

^a Values normalized using natural logarithm. Values followed by different letters represent significant differences (P < 0.05).

Factor	Tuber weight (g tuber ⁻¹)	Total number (tubers ha ⁻¹)	Total yield (Mg ha ⁻¹)	Tuber WW damage (%)
Nitrogen rate (kg ha ⁻¹)				
(NR)				
0	83.52 b	175,074 b	14.98 b	23.33 a
146	94.53 a	237,522 a	23.06 a	16.67 ab
180	95.30 a	254,786 a	25.06 a	21.39 ab
213	97.81 a	239,949 a	24.24 a	16.67 ab
247	97.87 a	242,498 a	24.69 a	16.11 b
Significance	< 0.001	< 0.001	< 0.001	0.0405
Planting date (PD)				
Early March	88.65 b	234,808 b	21.61 b	30.00 a
Late March	89.90 b	271,080 a	24.96 a	10.63 b
Early April	106.45 a	201,760 c	23.19 ab	7.50 b
Significance	< 0.001	< 0.001	0.0099	< 0.001
Timing of application (TA)	0.5790	0.4650	0.4076	-
PD x NR	0.7580	0.6870	0.6080	0.9419
PD x TA	0.5560	0.1140	0.0692	-
NR x TA	0.8150	0.4850	0.6933	-
PD x NR x TA	0.8590	0.9770	0.8780	-

Table 2.10. Effect of planting date, nitrogen rate, and timing of application on potato tuber yield and tuber wireworm damage for 2023 season in Painter, Virginia.

Values followed by different letters represent significant differences (P < 0.05). WW: wireworm.

Table 2.11.	Evaluation	of proposed	, traditional	planting d	lates, niti	rogen rat	te, and ap	plication
timing com	bination on	tuber total w	veight betwe	en March	and July	v 2023 at	Painter,	Virginia.

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Values followed by different letters represent significant differences (P < 0.05).

Table 2.12. Evaluation of proposed, traditional planting dates, nitrogen rate, and application timing combination on tuber total weight and estimated gross profit between March and July 2023 at Painter, Virginia.

Planting date	Nitrogen rate (kg ha ⁻¹)	Application timing	Total weight (Mg ha ⁻¹)	Avg. price at harvest (USD 22.6 kg ⁻¹)	Gross profit (USD ha ⁻¹)	Profit difference (%)
Late March	180	Early	25.13 ab	20.30	22,493.68	-
Early April	146	None	26.68 a	18.00	21,173.54	-5.9
Early March	146	None	20.33 b	23.60	21,156.94	-5.9
Late March	146	None	22.17 ab	20.30	19,846.96	-11.8
Significance			0.0368			

Values followed by different letters represent significant differences (P < 0.05).

Table 2.13. Performance on training and test data of wireworm injury level classification models for 2023 season in Painter, Virginia.

Model	Precision	Recall	F1	Accuracy	AUC ^a
Decision Tree (training)	0.90	0.75	0.76	0.80	0.80
Random Forest (training)	0.80	0.69	0.72	0.72	0.88
Decision Tree (test)	0.66	0.33	0.44	0.50	0.54
Random Forest (test)	1.00	0.50	0.66	0.70	0.75

^a Area under receiver operating characteristic (ROC) curve
Model	Precision	Recall	F1	Accuracy	AUC ^a
Decision Tree (training)	0.94	0.83	0.86	0.85	0.88
Random Forest (training)	0.71	0.83	0.69	0.63	0.73
Decision Tree (test)	0.67	0.67	0.67	0.60	0.58
Random Forest (test)	0.67	0.67	0.67	0.60	0.58
^a Area under receiver operat	ing character	istic (ROC) o	curve		

Table 2.14. Performance on training and test data of nematode presence level classification models for 2023 season in Painter, Virginia.

3. CHAPTER 3: EFFECT OF NITROGEN RATE AND IRRIGATION REGIMES IN POTATO PRODUCTION

3.1 Abstract

Irrigation is an essential element in crop production systems, responsible for providing plants with the necessary water and diluted nutrients for development. Potato growers in the Eastern Shore traditionally use overhead systems to irrigate potato plants, with irrigation regimens usually based on each farmer's experience. There is little consensus among potato farmers about the total amount of nitrogen (N) to be applied to the crop throughout the season, and no recommendations to adjust potato N rate in response to the selected irrigation regimen and system. Inadequate irrigation practices can lead to nutrient loss, increase disease development, and reduce plant growth and yield. Given the importance of increasing the efficiency of irrigation in potatoes, the objective of this study was to evaluate the effect of two irrigation methods regimens for overhead and subsurface drip irrigation and N rates in potato production. The study was established in a split-split plot randomized complete block design with 4 replications, with the irrigation system in the main plot, irrigation method in the sub-plot, and N rate on the sub-sub plot. Experimental plots consisted of 80 plants distributed in four rows. The evaluated irrigation systems were subsurface drip irrigation and overhead irrigation. For both systems, irrigation cycles were based on either crop evapotranspiration (ETc) or soil moisture content monitoring using soil water sensors (SWS). Total N rates used were 0, 56, 112, 168, 196, and 224 kg ha⁻¹. Fertilization was distributed in three applications: at planting, 30 days after planting (DAP), and 60 DAP. We collected plant emergence at 30 and 45 DAP and the number of days to the flowering stage for each plot. Soil nitrate levels were measured before

planting and 12 weeks after planting (WAP). Plant reflectance using multispectral drones was collected biweekly from 6 to 12 WAP. Harvest was collected at 110 DAP. The combination of overhead irrigation with ETc estimation resulted in improved plant growth, health indicators, and tuber yield. Key findings include strong correlations between the NDRE index and aerial-measured plant area with potato tuber yield, offering potential early yield prediction capabilities.

3.2 Introduction

Potatoes are one of the most valuable crops in the world (FAO, 2021). The United States is the fifth largest potato producing country and accommodates its commercial production in 30 states, including Virginia (National Potato Council, 2022; USDA & NASS, 2023). Potato production in Virginia is concentrated in the Accomack and North Hampton counties, where fresh white potatoes are most used. Potato growers in this region commonly use overhead irrigation systems to satisfy potato crop water needs. However, they rely on empirical irrigation regimes which could potentially be detrimental to the environment.

Irrigation practices in potato production play an important role in determining potato tuber yield and plant health. Optimum irrigation management requires a proper balance. Excessive irrigation can move important nutrients out of the potato rooting zone and amplify disease activity (Adams & Stevenson, 1990; Ahmadi et al., 2011; Djaman et al., 2021; Iwama, 2008; Marsh, 2019). In contrast, under-irrigation can impose stress upon the plants, which leads to significant yield reduction (Djaman et al., 2021; Onder et al., 2005). Irrigation in potato production can be carried out through several methods, including surface and subsurface drip systems to furrow and sprinkler systems. In terms of total tuber yield, the choice of irrigation method has been found negligible, provided the irrigation amount is correct (Da Silva et al.,

2018). Crop water requirements can be estimated through various methods such as evapotranspiration, which estimates water evaporated from soil and plants (Allen et al., 1998), soil moisture sensors, which continuously monitor soil water content, and multispectral images, which estimate crop evapotranspiration based on plant reflectance.

Beyond irrigation, N management plays a crucial role in potato production. Plants uptake N primarily through the application of synthetic fertilizers. Current N rate recommendations in Virginia range from 140 to 168 kg N ha⁻¹, but can go up to 269 kg N ha⁻¹ depending on field production potential (Reiter et al., 2009). Plant N levels are monitored through analysis of plant tissue for posterior correction through fertilization. (Alkhaled et al., 2023; Inoue et al., 2016; Muñoz-Huerta et al., 2013; Zheng et al., 2018). However, this process is time-consuming when monitoring large areas.

Remote sensing (RS) offers a compelling alternative to traditional plant health monitoring by delivering vast amounts of information a faster way with no direct contact (Alkhaled et al., 2023). RS consists in the analysis of reflected wavelengths of light, or reflectance, which is captured across various bands. Mathematical operations between these bands result in vegetation indices, which are powerful indicators of plant health and vigor. For instance, by mapping the Normalized Difference Red Edge (NDRE), areas with low values can be correlated to low N levels in plant tissue (Morier et al., 2015).

Given the importance of increasing the efficacy of irrigation in potato production in this region, an experiment was conducted with the following objectives: (1) to evaluate the effect of irrigation method, irrigation determination methods, and N rates on potato production and (2) to evaluate the relationship among different vegetation indices, N rates, and tissue temperature.

3.3 Materials and Methods

3.3.1 Experimental design

The study was conducted at Virginia Tech's Eastern Shore Agricultural Research and Extension Center in Painter, Virginia, between March and August 2023. The experiment was set up in a split-plot with the irrigation method as the main plot, irrigation determination as the sub-plot, and N rate as sub-sub plot factor with four replications. The sub-plots consisted of 80 plants distributed in four rows of 3 meters, with a spacing of 22.85 cm (9 inches) between plants and 91 cm between rows (3 ft). N rates evaluated were 0, 56, 112, 168, 196, and 224 kg ha⁻¹ distributed in three applications: at planting, at 30, and at 60 days after planting (DAP). Two distinct irrigation methods were evaluated: overhead irrigation and subsoil drip irrigation with irrigation regimens determined through ETc or SWS.

3.3.2 Crop management

The study site was classified as a Bojac sandy loam soil with a pH of 5.7, an organic matter content of 1.2%, and a nitrate concentration of 21 ppm (Figure 3.1). The selected potato cultivar for this study was Envol, a white, early season, and fresh market potato. Before planting, potato seeds were manually cut and treated with Mancozeb (ethylenebisdithiocarbamate) fungicide, at a rate of 1 kg/100 kg of cut seed. The potato seed pieces were mechanically planted while receiving applications of fungicides Ridomil Gold SL (mefenoxam, 420 g ha⁻¹), Quadris (azoxystrobin, 420 g ha⁻¹), and the insecticide Belay (clothianidin, 840 g ha⁻¹).

Throughout their growth cycle, potato plants were hilled, vine-killed, and harvested at 30, 100, and 110 DAP, respectively. Vine-killing was accomplished using the herbicide Reglone (diquat dibromide, 2.8 L ha⁻¹). To meet N requirements, fertilization was carried out through

mechanized base applications of liquid Urea containing 30% N, supplemented by manual applications of granular Urea. Additionally, to fulfill phosphorus (P) and potassium (K) requirements, triple superphosphate and potash were applied at rates of 56 and 112 kg ha⁻¹, respectively. The total rate for P and K fertilizers was fully applied at the time of planting Table 3.1.

3.3.3 Irrigation

Irrigation systems for both overhead and subsurface drip irrigation treatments were installed 7 weeks after planting (WAP). Overhead irrigation was applied using sprinklers (MEGANETTM), delivering water at a nominal rate of 3.33 liters per minute. Sprinklers were placed so two sprinklers irrigated each plot simultaneously (Figure 3.2). Subsurface drip irrigation was set using one drip tape per planted row, placed approximately 33 cm beneath the soil surface. The emitters on the drip tape were spaced at 30 cm intervals and delivered water at a rate of 0.03 liters per minute. Irrigation amount varied according to the determination method. For ETc treatments, irrigation was determined based on the cumulative evapotranspiration (ET) minus the accumulated precipitation, considering a constant crop coefficient (Kc) of 1. In contrast, for SWS treatments, irrigation amounts were determined by the data acquired from the soil moisture sensors. Both ET and precipitation were measured using a DAVIS Vantage Pro 2 weather station positioned 200 meters from the study site.

3.3.4 Data collection

Soil water content

Before planting and following field preparation, a soil sample was collected at 15 cm beneath the soil surface to construct its moisture release curve using HYPROP 2 equipment (Figure 3.3).

Additionally, critical water content levels were estimated using LABROS SoilView Analysis software. These critical levels included the soil's field capacity and wilting point (

Table 3.2), which served as essential targets for subsequent SWC monitoring.

Soil nitrate analysis

Soil samples for soil nitrate analysis were collected both before planting and at 12 WAP. Samples were collected using a soil probe inserted into the first 30 cm of soil at the center of each planted row. This process was repeated two to three times per plot in three replications, and the resulting sub-samples were combined to create a single representative sample per plot. Resulting samples were stored for 4 to 5 weeks in plastic Ziplock bags before being sent to a third-party soil laboratory for analysis (AgroLab).

Plant emergence and flowering

Plant emergence was monitored and recorded at 30 and 45 DAP. In addition, the days to first flower and days to reach 50% flowering were estimated by regularly inspecting the plots every two to three days after reaching the 40 DAP. Data was collected as described in Chapter 2.

Soil moisture monitoring

SWC was monitored every 15 minutes using Decagon 3TM or EC-5 sensors in conjunction with Em50 data loggers from 7 WAP onwards. Two sets of sensors, referred to as inner and outer sensors, were installed to capture soil moisture levels accurately. The inner sensors were installed at 7.5, 22.9, 38.1, 53.3, and 68.6 cm below the soil surface (Figure 3.4). Sensors were positioned at a 45° angle from the plant, directed towards the plant itself (Figure 3.5). Outer sensors were installed at depths of 22.9, 38.1, and 53.3 cm beneath the soil surface and set at a 45° angle from the plant, but oriented outwards (Figure 3.5). This arrangement of

inner and outer sensors formed a single SWC measuring point. A total of six SWC measuring points were installed, following the field placement diagram (Figure 3.2).

Aerial image acquisition and processing

Biweekly aerial images were captured from 6 to 12 WAP using two drones: a DJI Mavic 3M Enterprise drone and a DJI Mavic 3T Enterprise drone. The DJI Mavic 3M drone captured RGB bands and four multispectral bands: 560 ± 16 nm green (G), 650 ± 16 nm red (R), 730 ± 16 nm red edge (RE), and 860 ± 26 nm near-infrared (NIR) at an altitude of 46 meters above ground level. Meanwhile, The DJI Mavic 3T drone was equipped with an 8,000 to 14,000 nm infrared (IR) thermal camera and flew at 16 meters of altitude. Both drones were flown between 13:00 to 17:00 UTC and at their respective altitudes to achieve a ground sampling distance (GSD) of approximately 2.3 cm per pixel when orthorectified.

The collected RGB and multispectral images underwent a series of processing steps. Pix4D Fields software was utilized for 2D reconstruction and orthorectification of images collected with the DJI Mavic 3M drone. For thermal image orthorectification, Agisoft Metashape software was utilized. Multispectral images were radiometrically calibrated using the drone's integrated sun irradiance sensor. Subsequently, orthorectified RGB, reflectance, and thermal maps were aligned using QGIS software. Resulting maps were then merged, processed, and analyzed using the Python programming language. Processing steps included Minmax normalization of RGB bands, data extraction per plot, removal of soil values across all bands using binary masks, and computation of various multispectral indices as outlined in Table 3.3. Furthermore, the calculation of total plant area was performed by computing the area of pixels corresponding to plants considering the corresponding GSD.

Tuber yield

Tuber yield was assessed by categorizing tubers within predefined size groups according to USDA standards and measuring both the total number and weight of tubers in each category for every experimental plot. Tubers were categorized mechanically within four size groups according to diameter: A3 (greater than 8 cm), A2 (7 to 8 cm), A1 (5.5 to 6.99 cm), and B (4.5 to 5.49 cm). Tubers were then manually counted and then weighed using a scale with a precision of 0.02 kg. The resulting data was reported in multiple dimensions, including yield per plant, yield per plot, and yield per hectare.

3.3.5 Statistics and data analysis

The statistical analyses, models, and visualizations were constructed using R and Python programming languages within the Visual Studio Code software environment. For soil nitrate levels at 12 WAP and tuber yield data, analysis of variance (ANOVA) was employed to explore the impact of different factors on these variables. Wherever the ANOVA tests revealed significant effects of factors, post hoc analyses were conducted using Fisher's least significant difference (LSD) at a 5% level of significance to distinguish means. Furthermore, identification of potential predictors for total tuber yield was carried out using Pearson's coefficient of correlation. Subsequently, regression analysis was performed using the variable that exhibited the highest correlation value.

3.4 Results and Discussion

3.4.1 Soil, weather, and irrigation dynamics

In the assessment of soil, weather, and irrigation dynamics, several key observations emerged. From plant emergence until plant senescence, total precipitation (336 mm) represented 133% of total evapotranspiration (252 mm). This was mainly due to atypical heavy rains that occurred at the end of the season (Figure 3.6). Throughout this period, however, total irrigation amount for SWS and ETc treatments accounted for an additional 71 and 50 mm of water on average respectively. Regardless of the determination method, soil moisture levels remained over 30% (0.09 SWC) of the total plant available water (Figure 3.7 and Figure 3.8). However, these moisture levels are 20% below the recommendations, suggesting that optimal moisture was not maintained throughout the growing period (Djaman et al., 2021; Singh, 1969). Further challenges arose in early June when overhead systems stopped operating due to multiple malfunctions, leading to an increase in accumulated evapotranspiration for overhead-irrigated treatments (Figure 3.9 and Figure 3.10). Although soil moisture levels did not fall to critical levels in this period, it is possible that some degree of water stress may have been introduced. This stress could have potentially affected yield results, as described in previous research (Brocic et al., 2009; Djaman et al., 2021; Fabeiro et al., 2001; Karam et al., 2005; Kirda, 2002).

Analysis of soil nitrate levels at 12 WAP presented significant differences for only N rate and irrigation determination factors. Predictably, treatments with higher N rates showed elevated soil nitrate levels than those with low N rates or no application of N (Table 3.4). Considering the irrigation determination factor, SWS had significantly lower soil nitrate levels than ETc treatments (Table 3.4). The difference in irrigation amounts between determination methods in combination with the heavy rains could have influenced these results. This is consistent with studies showing that nitrates are prone to leaching in conditions of excess water (Ahmadi et al., 2011; Iwama, 2008; Jury & Nielsen, 1989; Marsh, 2019). Nevertheless, an average difference of 21 mm could be considered insufficient to alter soil nitrate concentrations significantly.

3.4.2 Plant growth and multispectral reflectance

Potato plants exhibited a consistent development, emerging by 4 WAP, reaching 50% flowering by 8 WAP, and undergoing senescence by 12 WAP. From 8 to 12 WAP, overheadirrigated plants, particularly with ETc estimation, showed significantly larger total plant area and NDVI values when compared to the rest of the treatments (Figure 3.11 and Figure 3.12). At 8 WAP, all treatments reached maximum plant area and NDVI reflectance, marking their maximum point of growth and health. Thereafter, total plant area and reflectance values declined rapidly, indicating that plants started senescing between 8 to 10 WAP. This is 2 to 4 weeks earlier than what Morier et al. (2015) reported when evaluating NIR reflectance in potatoes planted in Quebec, Canada. Although growing season in that region differs in time of the year in comparison to Virginia, their reported temperatures were very similar to the ones present during this study. This may indicate that other factors may have played a role in this early drop in reflectance values. One possible factor was the very act of fertilizing, which was performed using a disc liquid fertilizer spreader that caused foliar damage when plants were too large. It is possible that this equipment may have damaged the plants enough to affect these results. However, the degree to which it affected the plants was not measured.

The analysis of plant tissue temperature based on IR reflectance revealed that the combination of overhead irrigation and ETc determination consistently resulted in lower temperatures (Figure 3.13). This observation was true when plants were being irrigated and when they were not, although the difference in the latter condition was only 1°C (Table 3.5). These significantly lower temperatures may have reduced plant heat stress and increased yield potential as described by Tang et al. (2018). Additionally, low temperatures may have benefitted plant health and explain the observed higher values in NDVI and total plant area.

3.4.3 Tuber yield and yield prediction

The ANOVA test for total tuber yield weight and number resulted in significant differences for N rate, irrigation determination, and the interaction of irrigation method and irrigation determination factors. Total tuber weight and number showed no notable variation when using 112 kg N ha⁻¹ or higher N rates, except when compared to the control treatment (Table 3.6). Total yield based on size class remained consistent across N rate treatments (Figure 3.14). Moreover, ETc determination outperformed SWS determination method in total tuber number and weight (Table 3.6), although size class proportion of total yield was similar for these treatments (Figure 3.15). The combination of overhead irrigation with ETc determination resulted in the highest total tuber weight and number, compared with other treatments that had no significant differences in-between (Table 3.6). This is consistent with the total plant area, NDVI, and plant tissue temperature results previously described. However, average tuber yield for all treatments was approximately 14% below the expected target yield for this region (22.4 to 26.9 Mg ha⁻¹) (Reiter et al., 2009). Given that soil moisture levels fell below 50% and ETc irrigation determination accounted for 100% ET, it is possible that crop water requirements may have not been fully satisfied and water stress was induced. A similar result was presented in a study by Deblonde & Ledent (2001), which found that water stress reduced potato tuber yield by 17% in six cultivars, including early maturity potatoes, as cited by Djaman et al. (2021). Alternatively, tuber yield may have not reached the target yield due to the observed early senescence, which was potentially caused by the foliar damage during the second fertilization. Furthermore, ANOVA test results for average tuber weight indicated significant differences solely for the

irrigation method factor, in which overhead irrigation resulted in higher average tuber weight compared to subsurface drip irrigated treatments (Table 3.7). This could also be linked to the larger total plant area these treatments exhibited in comparison to the rest of the treatments (Figure 3.11).

Correlation analysis for identification of potential best predictors for tuber yield identified total plant area at 8 WAP as the highest correlator (0.85), followed by NDRE at 6 WAP (0.82) (Figure 3.16). Total plant area, as an indirect measurement of above ground biomass, is expected to be correlated to tuber yield (Milroy et al., 2019; Morier et al., 2015). On the other hand, our NDRE results are similar to what Morier et al. (2015) reported when evaluating the correlation of several vegetation indices with potato tuber yield. Their study found that NDRE and other RE reflectance-based indices were highly correlated with N in potato plant tissue and tuber yield. However, our correlation value for NDRE (0.82) is significantly higher to what they reported in their study (0.61). This was likely due to the data processing methods employed in ours, which removed soil values completely before calculation of indices for precise measurement and isolation of plant reflectance. Morier et al. (2015) did not report using a similar method.

Furthermore, best correlators for total tuber yield were identified as the maximum value of their respective variables. For this reason, subsequent regression analyses used maximum plant area and maximum NDRE as input variables for tuber yield prediction. As a result, two linear models were created with coefficients of determination (R^2) of 0.73 for maximum plant area and 0.65 for NDRE (Figure 3.177 and Figure 3.18). Applications of these models could potentially predict yield up to 8 weeks before harvest. However, further refinement and testing is required for real-world applications, as the relationships shown could be cultivar or location dependent. Moreover, the methods employed to obtain total plant area and NDRE values are sensitive to the presence of any other vegetation, such as weeds, which introduce noise into the

data. Although this was not the case during our study, it is likely that in real-world scenarios weed presence could significantly affect estimations using this approach.

3.5 Conclusion

Overhead irrigation combined with the ETc estimation demonstrated superior plant growth, health indicators, and tuber yield in comparison to other irrigation regimes. The consistently lower temperatures recorded with the overhead irrigation-ETc setup might suggest a reduction in plant heat stress, potentially leading to enhanced yield possibilities. However, yields across treatments were below regional expectations. External factors, like the potential foliar damage during the second fertilization and the inadequate soil moisture levels, could have stressed plants and affected tuber growth. Nevertheless, results suggest that current N rate recommendations should be maintained. These results showcase an advantage as most potato farmers in VA already have overhead irrigation setup in their farms. Additionally, there is little investment required to integrate ETc irrigation determination in their farms compared to SWS, making this recommendation economically feasible. Furthermore, RE reflectance-based vegetation indices and indirect measurements of plant biomass demonstrated to be good early yield predictors. Particularly, NDRE index and total plant area were strongly correlated with tuber yield. The refined data processing methodologies used in this study, especially the effective isolation of vegetation reflectance, might explain the enhanced correlation of NDRE to yield compared to previous findings. However, the derived linear models need further refinement and testing for application in real-world scenarios. Future research in search of optimization of irrigation practices in this region should explore determination methods as percentages of evapotranspiration.

3.6 References

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	Sufficiency Levels						
	Analysis	Deficient	Low	Sufficient	High		
pH	5.68						
Buffer pH	6.7						
Soluble Salts, EC mmho/cm	0.18						
Nitrate-N, ppm N	20.9						
Nitrate-N, Lbs N/A	50.00	-					
Depth	0 - 8 in						
Ammonium-N ppm	8.1						
Phosphorus, ppm P	319						
P Saturation	64			-			
UMD P FIV	350						
Potassium, ppm K	149						
Calcium, ppm Ca	565			÷			
Magnesium, ppm Mg	84						
Sulfur, ppm S	19						
Boron, ppm B	0.71			•			
Zinc, ppm Zn	1.75			•			
Manganese, ppm Mn pH sensitive	68.0						
Copper, ppm Cu	2.58						
Sodium, ppm Na	23						
CEC Sum of Cations, meq/100g	5.1						
H % Saturation	21						
K % Saturation	8						
Ca % Saturation	55						
Mg % Saturation	14						
Na % Saturation	2						
Organic Matter, %	1.2						
Organic Matter (LOI @ 455 C), %	2.08						
Est. Organic Carbon, %	0.68						
Aluminum, ppm Al	1000.0						
Iron, ppm Fe	230.0						

Figure 3.1. Soil fertility analysis pre-planting in March 2023 at Painter, Virginia.



Figure 3.2. Field placement diagram for soil water content (SWC) measuring points and microjet sprinklers between April to August 2023 at Painter, Virginia.



Figure 3.3. Soil water retention curve in LABROS SoilView Analysis software for the soil sample collected in March 2023 at Painter, Virginia.



Figure 3.4. Side view of inner (red) and outer (yellow) soil water sensor placement diagram.



Figure 3.5. Top view of inner (red) and outer (yellow) soil water sensor placement diagram.



Figure 3.6. Daily maximum and minimum temperature and daily precipitation data between early April and late June 2023 at Painter, Virginia.



Figure 3.7. Daily soil water sensor at 9 inches deep, precipitation, and irrigation data for soil water sensor determined irrigation treatments between late May and early July 2023 at Painter, Virginia.



Figure 3.8. Daily soil water sensor at 9 inches deep, precipitation, and irrigation data for evapotranspiration determined irrigation treatments between late May and early July 2023 at Painter, Virginia.



Figure 3.9. Daily accumulated evapotranspiration (ET), precipitation, and irrigation data for evapotranspiration determined irrigation treatments between late April and early July 2023 at Painter, Virginia.



Figure 3.10. Daily accumulated evapotranspiration (ET), precipitation, and irrigation data for soil water sensor determined irrigation treatments between late April and early July 2023 at Painter, Virginia.



Figure 3.11. Effect of irrigation method and irrigation determination in potato plant area growth curve between 6 to 12 weeks after planting in 2023 at Painter, Virginia.



Figure 3.12. Effect of irrigation method and irrigation determination on potato Normalized Difference Vegetation Index (NDVI) curve between 6 to 12 weeks after planting in 2023 at Painter, Virginia.



Figure 3.13. Effect of irrigation method and irrigation determination on plant tissue temperature curve measured with thermal drone between 6 to 12 weeks after planting in 2023 at Painter, Virginia. Temperatures at 10 WAP were measured while plants were being irrigated.



Figure 3.14. Effect of Nitrogen rate in total potato tuber yield per size class in 2023 at Painter, Virginia.



Figure 3.15. Effect of irrigation determination method in total potato tuber yield per size class in 2023 at Painter, Virginia.



Figure 3.16. Correlation matrix heatmap of variables highly correlated (>0.6) with total tuber yield in 2023 at Painter, Virginia. Values represent Pearson's coefficient of correlation.



Figure 3.17. Regression for total potato tuber yield as a function of maximum plant area measured with aerial images collected in 2023 at Painter, Virginia.


Figure 3.18. Regression for total potato tuber yield as a function of maximum Normalized Difference Red Edge (NDRE) index in 2023 at Painter, Virginia.

	.	.		At planting			30 DAP			60 DAP			Total	
Treatment	Irrigation	Irrigation		(kg ha^{-1})			$(kg ha^{-1})$			(kg ha^{-1})			(kg ha^{-1})	
number	methou		Ν	P_2O_5	K ₂ O	Ν	P_2O_5	K ₂ O	Ν	P_2O_5	K ₂ O	N	P_2O_5	K ₂ O
1			0	56	112	0	0	0	0	0	0	0	56	112
2			56	56	112	0	0	0	0	0	0	56	56	112
3		ET.	56	56	112	56	0	0	0	0	0	112	56	112
4		EIC	56	56	112	56	0	0	56	0	0	168	56	112
5			56	56	112	84	0	0	56	0	0	196	56	112
6	Drin		56	56	112	112	0	0	56	0	0	224	56	112
7	Dup		0	56	112	0	0	0	0	0	0	0	56	112
8			56	56	112	0	0	0	0	0	0	56	56	112
9		SWS	56	56	112	56	0	0	0	0	0	112	56	112
10		2442	56	56	112	56	0	0	56	0	0	168	56	112
11			56	56	112	84	0	0	56	0	0	196	56	112
12			56	56	112	112	0	0	56	0	0	224	56	112
13			0	56	112	0	0	0	0	0	0	0	56	112
14			56	56	112	0	0	0	0	0	0	56	56	112
15		FTe	56	56	112	56	0	0	0	0	0	112	56	112
16		LIC	56	56	112	56	0	0	56	0	0	168	56	112
17			56	56	112	84	0	0	56	0	0	196	56	112
18	Overhead		56	56	112	112	0	0	56	0	0	224	56	112
19	Overneau		0	56	112	0	0	0	0	0	0	0	56	112
20			56	56	112	0	0	0	0	0	0	56	56	112
21		SWS	56	56	112	56	0	0	0	0	0	112	56	112
22		2442	56	56	112	56	0	0	56	0	0	168	56	112
23			56	56	112	84	0	0	56	0	0	196	56	112
24			56	56	112	112	0	0	56	0	0	224	56	112

Table 3.1. Fertilization plan per treatment for experiment conducted between April and August 2023 at Painter, Virginia.

DAP: days after planting; ETc: crop evapotranspiration; SWS: soil water sensor

Level	Pressure (kPa)	Water content (%)
Field capacity	6	25.8
Field capacity	33	16.3
Wilting point	1500	4.7
Plant available water	-	21.1

Table 3.2. Water content estimates at various matric potentials for soil sample collected in March 2023 at Painter, Virginia.

Estimation using traditional constrained Van Genuchten-Mualem model (Van Genuchten, 1980).

Index Name	Abbreviation	Formula
Chlorophyll Index Green ^a	CIG	(NIR / G) - 1
Chlorophyll Vegetation Index ^b	CVI	NIR * R / G^2
Green Normalized Difference Vegetation Index ^c	GNDVI	(NIR - G) / (NIR + G)
Normalized Difference Red Edge ^c	NDRE	(NIR - RE) / (NIR + RE)
Normalized Difference Vegetation Index ^d	NDVI	(NIR - R) / (NIR + R)

Table 3.3. List of multispectral indices calculated and their equations.

Bands: green (G), red (R), red edge (RE), and near infrared (NIR) ^a (A. A. Gitelson et al., 2003), ^b (Vincini et al., 2008), ^c (A. Gitelson & Merzlyak, 1994), ^d (Tucker, 1979)

Factor	Soil Nitrate (ppm) ^a		
Nitrogen rate (kg ha ⁻¹) (NR)			
0	5.74 c		
56	8.24 bc		
112	9.36 ab		
168	8.97 ab		
196	10.58 ab		
224	14.03 a		
Significance	< 0.001		
Irrigation determination			
(ID)			
ETc	11.42 a		
SWS	8.02 b		
Significance	0.0063		
Irrigation method (IM)	0.1180		
NR x IM	0.7787		
NR x ID	0.8697		
IM x ID	0.5106		
NR x IM x ID	0.3447		

Table 3.4. Effect of irrigation method, irrigation determination, and nitrogen rate on soil nitrate levels at 12 weeks after planting in 2023 at Painter, Virginia.

^a Values normalized using natural logarithm. Values followed by different letters represent significant differences (P < 0.05).

Table 3.5. Effect of irrigation method, irrigation determination, and nitrogen rate in plant tissue temperature during active and inactive irrigation measured between 13:00 to 17:00 UTC in 2023 at Painter, Virginia.

	Tissue temperature (°C)				
Factor	8 WAP	10 WAP			
	(not irrigating)	(irrigating)			
Irrigation method (IM) x					
Irrigation determination (ID)					
Drip : SWS	28.97 b	33.13 a			
Drip : ETc	29.27 ab	32.63 a			
Overhead : SWS	29.52 a	29.67 b			
Overhead : ETc	27.92 с	27.74 с			
Significance	< 0.001	0.0059			
Nitrogen rate (NR)	0.8008	0.9196			
NR x IM	0.7636	0.7664			
NR x ID	0.3408	0.3287			
NR x IM x ID	0.5996	0.3300			

WAP: Weeks after planting; SWS: Soil water sensor; ETc: Evapotranspiration.

Factor	Total yield (Mg ha ⁻¹)	Total number (tubers ha ⁻¹)		
Nitrogen rate (kg ha ⁻¹) (NR)				
0	16.55 b	166,317 b		
56	18.74 ab	175,959 ab		
112	20.72 a	195,469 a		
168	19.48 a	189,115 a 190,386 a		
196	19.46 a			
224	20.41 a	191,731 a		
Significance	0.0106	0.0096		
IM x ID				
Overhead : ETc	21.75 a	203,766 a		
Overhead : SWS	17.79 b	170,577 b		
Drip : ETc	18.41 b	180,046 b		
Drip : SWS	18.97 b	184,929 b		
Significance	0.0059	0.0042		
NR x IM	0.8749	0.8326		
NR x ID	0.4756	0.1718		
NR x IM x ID	0.7212	0.8560		

Table 3.6. Effect of nitrogen rate, irrigation method, and irrigation determination on total potato tuber yield in 2023 at Painter, Virginia.

Values followed by different letters represent significant differences (P < 0.05). SWS: Soil water sensor; ETc: Evapotranspiration

Factor	Tuber weight (g tuber ⁻¹)
Irrigation method (IM)	
Overhead	105.62 a
Drip	101.60 b
Significance	0.0314
Irrigation determination (ID)	0.4231
Nitrogen rate (NR)	0.2046
NR x IM	0.9493
NR x ID	0.3154
IM x ID	0.6400
NR x IM x ID	0.7134

Table 3.7. Effect of irrigation method, irrigation determination, and nitrogen rate on average potato tuber weight in 2023 at Painter, Virginia.

Values followed by different letters represent significant differences (P < 0.05).

4. CHAPTER 4: CONCLUSIONS

Insights from the conducted experiments provided a comprehensive understanding of potato cultivation in the Eastern Shore of VA, focusing on planting dates, nitrogen application, irrigation techniques, and predictive methodologies. The combination of Late March planting with 180 kg of N ha⁻¹ led to optimal tuber yield and gross profit. In addition, concentrating most of the N application early in the season, while not significantly altering tuber yield, did improve vegetation indices associated with plant tissue N content and plant growth, especially for early April planted potatoes. This suggests that late planting dates might benefit from higher proportions of N at planting, while earlier planting dates did not respond to specific applications splits. Soil physicochemical properties, such as nitrate, Ca saturation percentage and H saturation percentage, emerged as significant predictors of wireworm damage levels. Similarly, K saturation percentage was identified as a potential predictor of nematode presence. The NDRE index was identified as an adequate predictor of N content in plant tissue, as well as for tuber yield when combined with multiple data processing methods involving masking techniques. Additionally, plant area was identified as a significant predictor of above ground dry biomass and tuber yield, potentially allowing for yield prediction up to six weeks prior to harvest. In terms of irrigation practices, overhead irrigation in conjunction with ETc estimation was found to be particularly beneficial for potato development. Our results further reinforce current N rate recommendations in this region with no influence of irrigation system selection or determination method. Overall, these results showcase a holistic system toward nutrient management and production system specifics for potatoes in VA. Our results not only refine current practices but also pave the way for future research, emphasizing system specific N management in

combination with advanced irrigation practices, and the development of robust predictive models for yield, pest damage levels, and presence of soil-borne pests. Overall, our proposed system of late March planting with current regional N recommendations could increase gross profits by 6% compared to current production systems in the Eastern Shore of VA. Additionally, overhead irrigation with ETc water requirement estimation pose as the most adequate irrigation regime to improve potato yield and plant growth while reducing environmental impact in the region.