ASSESSMENT OF PRECISION IRRIGATION ON POTATOES IN SOUTHERN ALBERTA

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Abstract

Precision irrigation, in which water is applied at different times and rates across and within farm fields according to environmental and soil conditions, offers a promising solution for effective water resource management. Excess irrigation can lead to disease and lower yields while under irrigation leads to a deficit often resulting in reduced yields and quality. Understanding water requirements is key to making informed irrigation decisions. Optimizing water usage for potato crops in southern Alberta is important in the face of water scarcity challenges. This project evaluates precision irrigation scheduling performance, including creation of management zones within a field, to determine which field variables have the most effect on potato yield, and analyze the effectiveness of predictive software. The data collected from five irrigated potato fields in Southern Alberta from 2019 to 2022, as well as from the Integrated Agriculture Technology Center (IATC) in 2021 and 2022, were analyzed. Annually, soil parameters, topography, moisture usage, and yield were evaluated at 5-6 monitoring points per field to represent variations within that field. Soil moisture at each point was monitored using moisture sensors and the Alberta Irrigation Management Model (AIMM) software was used to estimate evapotranspiration (ET) and soil moisture changes at the IATC site. It was revealed that topographic complexity had the most significant influence on soil moisture dynamics, resulting in significant effects on potato yield. Soil moisture had a significant positive effect on yield during the tuber bulking stage, especially at a depth of 0-35cm, but a significant negative impact at a depth of 35-60cm. While variations in growing degree days and soil complexity did not consistently affect yield, there was a tendency towards a negative effect. Moisture content variations among points at the IATC sites had no significant relationship with yield, indicating success in the ability of predictive scheduling and VRI in reducing this source of yield variability. The AIMM model demonstrated higher reliability in prediction of irrigation requirements in 2022 than 2021, possibly due to differences in factors such as soil organic

matter, bulk density of the soil, soil texture, weather, topography, and subsoil constraints, which affect model performance, but were not measured in this study. Precision irrigation offers a potential solution to address water scarcity challenges by optimizing water use efficiency and enhancing crop yield and quality through informed irrigation practices and technology integration.

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Dedication

This dissertation is dedicated to the people who made me the person I am today, supported me, and believed in me. Also, my parents, my husband Joel, and daughter Brooklyn, and all my instructors and mentors that have been encouraging me throughout my education and career!

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LIST OF ABBREVIATIONS

AGRASID – Alberta Soil Information Viewer

AIMM – Alberta Irrigation Management Model

AM – Percentage Available Moisture

ERZ – Effective Root Zone

ET - Evapotranspiration

ET_0 – Reference Crop Evapotranspiration

FC – Field Capacity

GDD – Growing Degree Days

GIS – Geographical Information System

GWC – Gravimetric Water Content

Kc – Crop Coefficient

IATC - Integrated Agriculture Technology Center

IMCIN - Irrigation Management Climate Information Network

PI – Precision Irrigation

RMSE – Root Mean Square Error

SSIM - Site-Specific Irrigation Management

SSRB - South Saskatchewan River basin

TPI - Topographic Position Index

TWI - Topographic Wetness Index

UAV - Unmanned Aerial Vehicle

VRI – Variable Rate Irrigation

VWC - Volumetric Water Content

WP – Wilting Point

WUE – Water Use Efficiency

1 INTRODUCTION

Southern Alberta is a semi-arid region with extensive irrigation infrastructure that allows growers to produce a wide variety of specialty crops, including potatoes. In the Lethbridge (AB) area, the average seasonal crop water demand for potatoes is between 400 to 550 mm per year (Agriculture and Forestry, 2016), whereas the average yearly rainfall is around 300 mm (Environment and Climate Change Canada, 2020). This deficit is made up by irrigation water provided by the Oldman and Bow Rivers, including their tributaries. The water provided by these two rivers has been fully allocated since 2000, and they have been closed for new water withdrawal licenses. A water trading system was implemented to encourage further regional development within water boundaries (Pentney, Ohrn, 2008). Annual water usage is similar in potatoes to other specialty crops; however, potatoes are subject to a higher sensitivity to water stress (Shock et al., 2007). Insufficient irrigation during different times in the season can result in multiple effects such as smaller numbers of tubers per stem (Aliche et al., 2018). Potato plants are particularly sensitive to water stress during tuber bulking and ripening (Fabeiro et al., 2001). Alternatively, if the field is over-watered, the risk of disease increases and can result in a loss of tuber yield and quality (Shock, 2007). Potatoes are further limited by a rooting zone of only 0.6 m compared to cereal and oilseed crops that have an effective 1 m rooting zone. Implementing improved irrigation management techniques can increase water use efficiency, prevent deficit conditions or excessive irrigations, and overall improve potato productivity and sustainability of the industry (Yari et al., 2020).

There are a wide variety of methods used by Alberta producers to manage their irrigation. More advanced methods used may include determining actual plant water use with evapotranspiration-based models. Other common methods include the hand feel method, using a fixed uniform irrigation schedule, or adopting recommendations of a contracted agronomist. A small number of producers have their own soil moisture sensors (Agriculture and Forestry, 2016). Precision irrigation technology is another method that is being adopted by producers. This consists of precisely allocating in-field irrigation based on data collection and diagnostic tools (Nicol, Nicol, 2021). This may consist of precision application tools such as variable rate irrigation, which allows producers to use spatial data to create prescriptions and vary irrigation application rates accordingly. A study done on irrigated farms in southern Alberta found that, on average, greater than 80% of producers were implementing some type of precision technology on their farms (Nicol, Nicol, 2021). However, most of the precision approaches employed do not consider variability in soil properties among and across fields as they affect water need. Adopting best management practices by using precision irrigation or site-specific irrigation management to account for variability in the soil texture, topography across a field, can further water and energy savings and optimize yield (King et al., 2006). Implementing site specific irrigation management often requires additional hardware, labor, and it is necessary to have detailed information on soil and crop water requirements in each field management zone identified (King et al., 2006). The increased labor requirement, lack of knowledge on how to implement precision technologies as well as the high cost of the equipment are the major barriers preventing adoption (Nicol, Nichol, 2021). In fields with high variability, the use of irrigation water scheduling tools that are sensitive to meaningful climate and soil variations and implementing site-specific irrigation management rather than uniform irrigation management could be highly beneficial (Yari et al., 2020). The potential added value of this practice is currently poorly quantified in Alberta (Nicol, Nichol, 2021).   It is also unclear which practices can be adopted in a practical manner by producers, as their success depends on the producer's ability to utilize the technologies available.

As climate change becomes an increasing concern, paired with a growing population and resulting in intensifying competition for water resources, moving to more efficient irrigation management strategies is more important than ever (Boluwade et al., 2016). Irrigated crop production is one of the world's major uses of freshwater (Boluwade et al., 2016). With limited freshwater available for irrigation and ever-increasing demand for irrigated acres, managing our current water allocation to its highest efficiency will benefit all producers, and help withstand future water availability challenges.

The main objectives of this project were to evaluate precision irrigation water application to examine relationships between soil water, soil properties and potato yield to determine key factors that farmers need to consider when employing precision irrigation strategies, and to evaluate the performance of precision irrigation approaches including scheduling methods based on evapotranspiration predictions and variable rate application across fields.

The study presented in this thesis addresses the use of precision irrigation and investigates precision irrigation approaches used to schedule irrigations. The following research questions guided this component:

1. How do soil hydrological conditions, topography, climate, and soil characteristics affect yield of potatoes?
2. How effective are predictive irrigation technologies at predicting soil moisture in a variable field?

I hypothesize that soil and hydrological conditions that vary among and across irrigated potato fields drive potato yield. Precision irrigation scheduling technologies that account for these variations will effectively predict soil moisture changes and improve water use efficiency and yield.

This thesis describes research presented in two chapters, each of which was written as a standalone manuscript for publication. Chapters begin with a preface explaining how that chapter relates to the thesis and includes a summary of the research, a brief introduction, a detailed materials and methods section, a summary and discussion of the results followed by the conclusions.

The current chapter (Chapter 1) provides the introduction while Chapter 2 forms a general literature review of the subject to serve as background. Chapter 3 presents research work related to the effect of *Soil Hydrological Conditions on Potato Yield in Southern Alberta*. Chapter 4 examines the effect of *Precision Irrigation Methods on Variations in Water Use Efficiency and Yield on Potatoes in Southern Alberta*. The research chapters (Chapters 3–4) are followed by a synthesis (Chapter 5) that connects the research described in the two manuscripts, summarizes the major findings and implications of the research, and highlights the combined contributions of the individual studies. This chapter also includes a conclusions section together with suggestions for further research. Literature cited in the literature review and throughout the thesis are listed in the Reference section that follows Chapter 5.

2 Literature Review

2.1 IRRIGATION IN AGRICULTURE

As the world population increases, global water withdrawals have also increased to sustain the higher food demand and rising standard of living (Wada et al., 2014). To safeguard water supplies and ensure an adequate supply of freshwater worldwide for fibre, food, and bioenergy production, continued improvement of irrigation efficiencies on farm and within irrigation water distribution systems is essential (Bennett et al., 2015). Implementation of more efficient irrigation management systems has become ever more critical as the world population increases, compounded by pressures due to climate change and a greater competition for water resources (Boluwade et al., 2016). Around 70% of the world's water withdrawals are used for irrigated agriculture, which in turn accounts for about 40% of global food production on less than 20% of cropped land (Food and Agriculture Organization of the United Nations [FAO], 2011; Wada et al., 2014). With the world population predicted to reach 9.8 billion by 2050 it is essential to continue to improve efficiencies. There is also an increasing demand for freshwater supplies from urban and industrial users, which will result in increased competition for the limited water resources with agriculture (Bennett et al., 2015).

2.2 IRRIGATION IN ALBERTA

In southern Alberta there are 11 irrigation districts that manage approximately 2,868,938 acre-feet of surface water and provide irrigation water to 85 % of the 1,682,302 acres of irrigated land in southern Alberta (Government of Alberta, 2023a). The irrigation districts provide water for irrigation through an extensive infrastructure that includes over 8000 km of conveyance works, 170 major structures, and approximately 4700 km of drainage works (Bennett et al., 2015; Government of Alberta, 2023a). This represents a total investment cost of over CAD $3.6 billion (Bennett et al., 2015). The remaining 15 % of irrigated area in Alberta is made up of small private irrigation projects (Kamar, Klein. 2014; Government of Alberta, 2023a). Irrigated agriculture in southern Alberta withdraws about 75% of the surface water allocation in the South Saskatchewan River Basin (SSRB) in Alberta, meaning that even a minor improvement in irrigation efficiency has the potential to save significant amounts of water (Kamar, Klein. 2014). Estimations suggests that improving irrigation efficiency by 4.6% could conserve enough water to meet the total annual requirements of all municipalities in the SSRB (Kamar, Klein, 2014).

In 1969, the Government of Alberta initiated a cost-shared Irrigation Rehabilitation Program to rehabilitate irrigation water delivery infrastructure which has invested over CAD $1 billion to improved water conveyance efficiencies (Bennett et al., 2015). This has allowed irrigation districts to expand their irrigated areas due to improvements in infrastructure and water conveyance operations, as well as more efficient on-farm systems (Bennett et al., 2015). In 2020, the Alberta Government announced a historic investment in irrigation infrastructure of $815 million directed to further improve water delivery infrastructure and increase overall water storage capacity. This will consist of a contribution of approximately $407.5 million by the Canada Infrastructure Bank, while the Government of Alberta and the irrigation districts will contribute $244.5 million and $163 million, respectively (Government of Alberta, 2020). This project will focus on increasing the efficiency of water conveyance in 8 irrigation districts, allowing expansion of irrigated acres using the same amount of water (Government of Alberta, 2020).

Over the last 50 years, there has been a shift in irrigation technology from flood irrigation to side-roll sprinkler systems, high-pressure pivot systems, and most recently to the low-pressure pivot systems (Agriculture and Forestry, 2016). The use of sprinkler irrigation accelerated after the 1970s, and the use of low-pressure centre pivot systems has become primary technology used by irrigators today

(Wang et al., 2015). Currently most irrigated acres in southern Alberta are irrigated using low-pressure centre-pivot irrigation systems, with the rest irrigated with high-pressure centre pivots, wheel-move systems, gravity, and other methods (Bennett et al., 2015; Government of Alberta, 2023a). This shift in irrigation technologies has resulted in an increase in application efficiencies from approximately 40% application efficiency with flood irrigation, to an application efficiency for wheel-move sprinklers of 70%, to high-pressure pivots at 73% and low pressure-centre pivots at 84% (Wang et al., 2015). While the improvement in moving to more efficient equipment has already substantially improved efficiencies, it will be necessary to continue find ways to stretch a limited water supply. Improved on-farm management of current allocations will be fundamental in improving efficiencies once the most efficient irrigation systems are purchased.

2.3 IMPORTANCE OF IRRIGATION IN SOUTHERN ALBERTA

When plants experience an excessive water deficit during the growing season, there is normally a substantial drop in crop yield and quality (King et al., 2006). When crops are stressed for water it decreases plants water potential, inhibits photosynthesis, and reduces growth (Bennet, Harms, 2011). Bennett and Harms (2011) investigated the relationship between major irrigated crops grown in southern Alberta and their relationships to evapotranspiration. They found that maximum potential yield for most irrigated crops in Alberta has improved significantly over the past 30 years, and that there are linear relationships between crop yield and field water supply. Ensuring the proper application amount at the correct time for crop growth and development is essential to achieve maximum economic return and achieve optimum water use efficiency (King et al., 2006). In southern Alberta's semi arid climate, precipitation amounts vary erratically from year to year, with about 70% of annual precipitation falling within the growing season. Precipitation in Alberta ranges from over 700 mm annually in the mountains (Fig. 2.1.), with much of it falling as snow in winter, while in the south-eastern part of the province precipitation decreases to about 270 mm a year. Higher summer temperatures are also observed in the southeastern part of the province. These factors, combined with generally high winds, give this region the greatest potential for water deficits (Agriculture and Rural Development, 2010). Supplemental irrigation enables higher and more stable crop production, as well as the cultivation of a wider variety of crops (Hao et al., 2001). There are currently more than 60 types of crops grown in Alberta, including 28 specialty crops and include potatoes, sugar beets, dry beans, various vegetable crops and more (Agriculture and Forestry, 2020; Government of Alberta, 2023a). Irrigation is necessary to produce row crops and other specialty crops due to their high consumption of water, which exceeds the amount provided by rainfall in this region (Hao et al., 2001).

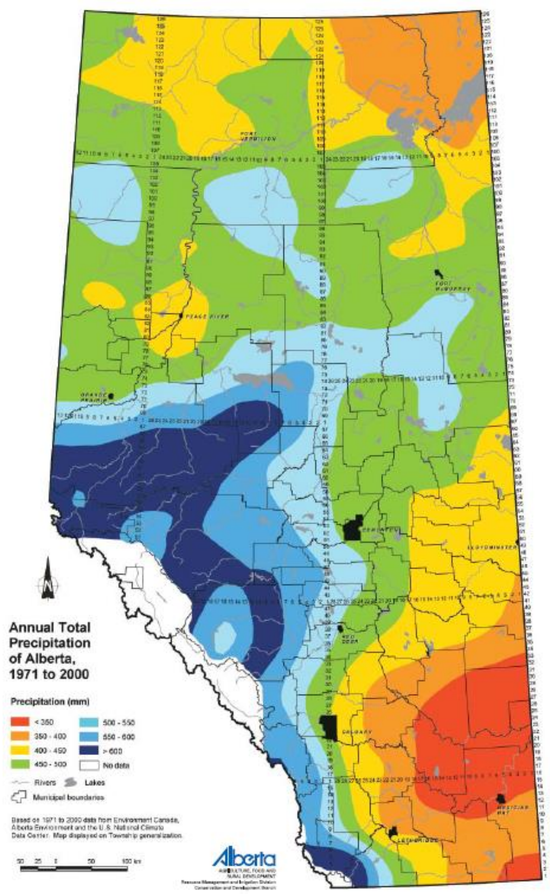


Fig. 2.1. Mean annual precipitation across Alberta from 1971 to 2000 (Chetner et al., 2003).

The irrigation industry in Alberta plays an important role in the economic and social well-being of the region (Alberta Agriculture and Rural Development, 2014). The extensive variety of crops grown in Alberta that cannot be cultivated under dryland conditions creates new markets that contribute to the province's economy (Paterson Earth & Water Consulting Ltd, 2015). Irrigation infrastructure also provides water to the processing industries that utilize the high-value irrigated crops grown in Alberta such as potatoes, as well as many confined livestock operations (Alberta Agriculture and Rural Development, 2014). Irrigation infrastructure in Alberta is also important for providing water to towns and villages. Irrigation reservoirs also serve as wildlife habitats and recreation facilities throughout the southern region. The irrigation industry recognizes the significance of improving water conservation, efficiency, and productivity to effectively manage current water resources (Alberta Agriculture and Rural Development, 2014).

2.4 OPPORTUNITIES AND CHALLENGES OF IRRIGATION IN ALBERTA

The access to irrigation offers many opportunities to producers in Alberta. Having the ability to eliminate moisture as a limiting factor allows for the diverse variety of crops that are currently produced in the province. Irrigation offers many well-known benefits to on-farm production, including yields that are commonly two to three times higher than dryland, particularly in the drier areas of the province, as well as more stable and reliable yields and quality. Further benefits are increased diversification, and production of crops that can only be grown under irrigation (Irrigation Water Management Study Committee, 2002). Irrigation in Alberta allows a wide range of cereal, oil seed, forage, and specialty crops to be produced (Alberta Agriculture and Rural Development, 2014; Government of Alberta, 2023). Decades of research have improved plant genetics, and combined with efficient irrigation and agronomic practices there has been a substantial increase in potential yield and quality for crops grown under irrigation in this area (Bennett, Harms, 2011). Many of the high value crops grown are processed into value-added products that are consumed worldwide (Alberta Agriculture and Rural Development, 2014). There are many processing facilities for these products in Alberta that provide opportunities for employment as well as other economic opportunities (Paterson Earth & Water Consulting Ltd, 2015). The economic impact of primary production on irrigated land in Alberta is greater than expected, despite only 4% of crop land being irrigated. This sector generates over 14% of farm cash receipts, about 11% of agricultural value-added, and 19% of direct agricultural employment (Irrigation Water Management Study Committee, 2002).

The economic development resulting from a strong irrigation industry presents several challenges. The industry must continuously adapt to situations that develop related to the use, management, and available quantities of water (Alberta Agriculture and Rural Development, 2014). This competition is constantly increasing due to the rising demand for quality water resulting from population growth, economic development, and societal expectations regarding the environment and health (Alberta Agriculture and Rural Development, 2014). This growth and increased competition necessitated the closing for any additional water license allocations in 2006 (AMEC Earth and Environmental, 2009). The overall supply is also affected by considerable variation from year to year, which is dependent on annual mountain snowpack and precipitation (Agriculture and Rural Development, 2010). These water supplies may be reduced further due to climate change, resulting in higher temperatures, increased evapotranspiration, and changes in precipitation timing and amounts (Bennett, Harms, 2011). Predicting future water supplies is challenging due to the uncertainty of the effects changes that will happen in temperature and precipitation, making the future of irrigation unpredictable (Agriculture and Rural Development, 2010)

Another challenge related to irrigation is the increased input cost and requirement, including fertilizers, pesticides, irrigation equipment and other farming equipment. Inputs may be required in greater quantities than under dryland production, and proper equipment is essential to realize the full benefits of irrigation (Irrigation Water Management Study Committee, 2002). Annual cost for machinery alone can be anywhere from about $1,200/ha for seed canola to about $4,900/ha for crops that require more specialized equipment such as potatoes and sugar beets (Paterson Earth & Water Consulting Ltd, 2015). A study done by Bjornlund et al. (2009) found that producers in southern Alberta were not implementing changes to more efficient equipment and management practices due to financial constraints, and many producers did not realize the value of implementing them on their farm.

2.5 POTATOES IN SOUTHERN ALBERTA

Potatoes have similar water requirements to other crops grown in the area; however, they are more sensitive to water stress. Excessive or deficit soil water conditions during the growing season normally has a substantial adverse affect on crop yield and quality (King et al., 2006). Potatoes require a relatively narrow range of soil moisture (65-100% available moisture) throughout the growing season to achieve maximum yield and quality (Alberta Agriculture and Forestry, 2011). Due to this, potato production in Alberta is highly dependent on irrigation water supplies to produce high yields of marketable potatoes (Stark et al., 2013). To achieve maximum yield and quality, potatoes grown under optimal conditions will require between 400 to 550 mm of water per growing season in southern Alberta (Alberta Agriculture and Forestry, 2016).

In irrigated potato management there has been increased interest in conservational practices as growers seek more efficient methods of production (Khakbazan et al., 2017). Maximum efficiency in the utilization of available water in potato production requires the use of irrigation management practices that will promote both increased tuber yield and quality for processing with the least amount of water used. This means using irrigation water efficiently, along with precipitation and stored soil water for production (Efetha et al., 2011).

Demand for potatoes from potato processing facilities along with limited irrigation water available encourages producers to meet the water requirements of potato crops to achieve high potato quality and yields despite the limitations. The potato industry has served a prominent role in agricultural production in southern Alberta over the past two decades, contributing over $2.87 billion of economic value to the Alberta economy (PGA, 2023). Alberta has become the largest exporter of seed potato in Canada and is also a major contributor of potato to the food processing industry (Khakbazan et al., 2017). Potato production in Alberta has grown from only 5812 ha of potatoes grown in the late 1990’s, to 16,523 ha grown in 2003, to 22,650 ha grown in 2012 (Larney et al., 2016)., to approximately 27,316ha in 2021 (Potato Growers of Canada, 2021). In 2022, 1.36 million tonnes grown on 28864 ha within Alberta (PGA, 2023). This rise has been attributed to the addition of potato processing plants in southern Alberta starting in the late 1990’s (Larney et al., 2016).

Various research trials have been conducted exploring improved irrigation management and water saving practices in potatoes. Harms and Konschuh (2010) worked to improve irrigation efficiency by altering the standard hill shape to one with a wider profile or a flattened top, to allow more of the applied irrigation water to infiltrate into the hill before it ponds in the furrow. They found that producers can achieve up to 10% water savings by modifying the hill shape to either flat-topped or wide-bed hill shape. Such WUE improvement strategies have been implemented in various studies on irrigated crops to improve yield per unit water consumed or applied. Steele et al. (2006) compared the effect of furrow position of a modified ridge/furrow system to conventional standard hill-planted potatoes on yield and quality. A significantly greater potato yield with larger size were harvested from furrow planted compared to hill planted potatoes. They also found that there was greater soil water in the furrow position than in the hill. Using site specific irrigation management compared to uniform irrigation management could be highly beneficial, especially in fields with high variability. The potential added value of this is currently poorly quantified in Alberta.

2.6 IRRIGATION MANAGEMENT IN ALBERTA

Irrigation management plays a critical role in ensuring long term sustainability of irrigated agriculture in Alberta. Effective irrigation management in Alberta ensures the sustainable utilization of water resources, improves crop yields, and supports food production (Alberta Agriculture and Rural Development, 2014). The focus on irrigation management is primarily considered on a local scale, however, proper management of irrigation in Alberta can have an impact on a global scale as well. Optimization of water use on the local scale by employing efficient irrigation methods can reduce water wastage and enhance agricultural productivity which will ultimately contribute to global food security (Food and Agriculture Organization of the United Nations, 2017). As climate change impacts the availability of water and patterns globally, implementing effective irrigation management becomes increasingly important. By implementing technologies for saving water and adopting efficient irrigation strategies to adapt to the changing climatic conditions, Alberta can contribute to climate change mitigation efforts and serve as a role model globally for adaptation measures in the face of water scarcity and changing environmental conditions (Government of Alberta, 2023b).

Alberta's semi-arid climate and limited rainfall, along with limited access to water for irrigation and an ever-increasing demand for irrigated acres make irrigation management more important than ever. Net irrigation water requirements tie directly to the crop water demand and precipitation amounts. These net amounts will vary depending on weather conditions, efficiency of the application of the system and how it is being managed (Bennett et al., 2015). Air temperature, relative humidity, wind speed, precipitation amount and frequency, crop growth stage and crop management are all factors that determine crop water demand (Efetha et al., 2011). The gross water demand is the total amount of water needed to meet crop water demand considering the irrigation system application efficiencies, as well as water conveyance losses such as return flow, evaporation, and seepage (Bennett et al., 2015).

Considering a combination of all these factors, producers can begin to create an irrigation management program that will provide their crop with optimum water supply over the growing season, ideally matched to variations across the field that control soil available water.

Effective irrigation management practices are essential for optimizing water use efficiency and to improve overall crop productivity and environmental considerations. A study done by Nicol et al., (2010), found that prior to 2001, 74% of producers were basing irrigation decisions on when and how much water to apply using visual inspection of condition of the crop. In this study, 27% of producers used the hand feel method, 11% used soil moisture monitoring equipment, 6% used evapotranspiration methods, and 19% used private consultants for irrigation application decisions. The overlap is from producers that used multiple methods. As irrigation methods and efficiencies have improved, producers are also finding value in adopting more efficient methods of irrigation management and technologies. In a more recent study done by Nicol and Nicol (2021), they found that 72-82% of producers in three different irrigation districts are moving towards the adoption of multiple approaches to support application decisions that contribute to more precise and efficient use of water. They found these adoption rates to be relatively high compared to other studies. Nicol et al., (2010) noted that the reduction in water and energy use was a prime factor in encouraging producers to improve their scheduling approach. Increased yield and reduced cost were a clear dominant factor in the various motives of producers to adopt better technology. However, though most producers identified that reduced water use was important to them, it was not identified as a key factor in their decisions. This was primarily caused by producers indicating that they already use all the water saving practices that are practical for them to use, or that the cost of being more efficient was not economically viable on their operation.

In addition to irrigation management practices, irrigation equipment is equally important in achieving maximum water use efficiencies. Application efficiencies vary between systems and depend on many factors: type of irrigation system, age of the system, type of nozzles, height of the sprinklers above the crop canopy, upkeep of the system, design of the field (gravity irrigation), size of the stream (gravity irrigation), type of crop and growth stage, irrigation management, environmental factors, and numerous other soil, crop, weather, and agronomic variables. Irrigation application efficiency is affected by application losses that include wind drift of irrigation water, evaporation of water before infiltration into the soil, surface runoff from the field, and deep percolation of applied water below the crop rooting depth (Agriculture and Forestry, 2016).

As more efficient methods continue to be adopted, there is still low efficiency of irrigation water use and uncertain sustainability in water supply to many regions (Khakbazan et al., 2017). Moving to the predominant low-pressure low-energy center pivot irrigation systems has partially overcome these issues; but these systems are commonly used to apply a uniform rate of water across the entire field, which does not account for the variation in soil properties, topography or other factors that affect available water to the crop (Khakbazan et al., 2017). Variable rate irrigation (VRI) is a technology that allows the application of irrigation water to be tailored according to crop needs and soil physical and chemical properties. A prescription can be created based on variability in water usage across the field due to the different soil properties, topography and other factors that affect crop water usage to allow differentiated, precise applications of irrigation water (Yari et al., 2017). With the increased competition for the limited water available in southern Alberta the goal of using the most efficient methods possible will require implementation of irrigation management practices that promote both increased yield and water conservation (Efetha et al., 2011).

While it may not be viable for all producers to move to variable rate systems, significant water savings can be achieved by applying only what is necessary to meet crop ET needs, while still achieving maximum yields. By using an irrigation scheduling program based on in field conditions, and implementing precision irrigation technologies such as moisture sensors, variable rate irrigation, remote sensing and weather stations, further irrigation efficiencies can be achieved (Burt et al., 1997). With limited water supply and increased demand for irrigation water, producers must make good irrigation decisions that will optimize water use efficiency. To achieve this, they must have an effective irrigation scheduling system that will guide when and how much irrigation water to apply to the crop to meet specific crop needs. Bennet et al. (2015) and Yari et al. (2020), emphasized the importance of using evapotranspiration-based methods, such as reference crop evapotranspiration (ET_0) and crop coefficient (K_c), to determine irrigation timing and amounts accurately and allow for the optimization of water use efficiency.

Estimating crop water requirements with reference evapotranspiration using the Penman Monteith reference crop method and crop coefficients is currently the commonly used and validated evapotranspiration-based calculation (Olberz et al., 2018) used in various types of irrigation scheduling software. This method requires measured meteorological observations including maximum and minimum air temperatures, solar radiation, maximum and minimum relative humidities, wind speed, as well as site details of latitude and altitude to calculate crop water requirements (Valiantzas, 2013). Reference evapotranspiration is the rate at which readily available soil water vaporizes from a uniform surface of dense, actively growing vegetation having specified height and surface resistance, not short of soil water, and representing an expanse of at least 100 m^2 of the same or similar vegetation. The reference surface has been expressed as a hypothetical crop surface that has specific characteristics (Allen et al., 2004). These reference evapotranspiration values are used in conjunction with crop coefficients to estimate crop and vegetative water use and water requirements. The crop coefficients represent crop type and development (Hargreaves, 1994).

Evapotranspiration (ET) is complicated to directly measure. Methods are often expensive and require highly accurate measurements and can only be fully exploited by well-trained research personnel. Common methods of measuring ET are using lysimetry or using advanced atmospheric measurement technology such as eddy covariance (Uddin et al., 2013). Due to the difficulty of obtaining accurate field measurements to directly assess ET, there are various models that compute ET from weather data using the Penman Monteith equation (Allen et al., 1998). Some of the tools currently available are Alberta Irrigation Management Model (AIMM), IRRI-cast, FieldNET, and others.

2.6.1 Evapotranspiration -based models for managing irrigation applications

IRRI-cast is a web-based calculator that is a decision-support tool that uses data from the nearest meteorological station to assist in on-farm irrigation scheduling operations in Alberta. The IMCIN calculator, known as IRRI-Cast, uses the modified Penman Monteith equation to estimate crop ET. Information available from this web-based calculator is like various other tools that have been designed to assist irrigators with irrigation scheduling (Agriculture and Forestry, 2016). This calculator can be used to estimate daily ET values based on crop type and seeding date. These ET values can then be used to base irrigation decisions on a replenishment basis. By understanding how much water the crop has lost through ET one is able to replace it as needed. The calculator uses the same approach as another model: AIMM (Alberta Irrigation Management Model); however, the calculations in IRRi-Cast are done by the producer, and predictions are not as detailed or considered as accurate as AIMM.

FieldNET is a water-based management decision-support tool that gives producers the ability to control their irrigation systems remotely, and provides real-time information, and enhanced reporting. This is a subscription-based tool that provides producers with the ability to monitor field-centric soil moisture and weather and optimize water-use through integration with VRI plans. Through the usage reports generated by this model, farmers can predict when, and how much to irrigate. They also provide the option and ability to connect to a soil moisture monitor to provide feedback based on actual soil moisture (Southern Irrigation, 2018). This technology is very popular among producers and is widely used to remotely control pivots.

A model that has been used for many years in Alberta is the Alberta Irrigation Management Model (AIMM). This model estimates daily crop ET and soil moisture predictions, offering potential time savings with less field visits, as well as energy and water savings (Agriculture and Forestry, 2016) that can be achieved from application of the model. Meteorological parameters that affect ET such as temperature, solar radiation, relative humidity, and wind speed, are used in the modified Penman Monteith method to estimate ET for a well-watered reference crop. Daily and cumulative ET is estimated and adjusted to the crop of interest using a crop coefficient determined by measuring actual crop water use of that crop in southern Alberta. The meteorological parameter variables used in AIMM are downloaded from the Irrigation Management Climate Information Network (IMCIN) weather stations located in the irrigated areas of Alberta (Agriculture and Forestry, 2016). This model also takes into consideration other factors such as seeding date, crop type and soil texture to tailor predictions to crop needs. The software then generates irrigation recommendations based on these values. A study done by Yari et al., (2020) used AIMM to estimate frequency and depth of irrigation levels for potatoes and was considered reasonably accurate. The software was used in conjunction with measured soil moisture conditions and used to adjust the model generated numbers to ensure accurate predictions.

2.7 PRECISION IRRIGATION

As water scarcity issues continue in southern Alberta, more efficient methods of irrigating are being sought after. The use of precision irrigation is a promising approach that allows producers to improve water use efficiency while optimizing crop productivity. Precision irrigation is a practice that involves to delivering water to crops in a targeted and precise manner, based on conditions specific to individual fields. It involves optimizing water application, minimizing losses, and maximizing water use efficiency through tools such as drip irrigation, soil moisture sensors, and remote sensing (Smith et al. 2011). Precision irrigation methods use data collection, diagnostic and application decision support tools to precisely apply the required inputs on irrigated fields. The adoption of these precise application methods has become a major contributor to more efficient water management in southern Alberta (Aubert et al., 2012; Nicol, Nicol, 2021).

Conventional irrigation practices have traditionally been used which uses mean values of crop needs within that field to determine a uniform irrigation application amount and time. This does not consider any variation within the field such as changes in soil texture, topography and density that affect soil water retention and availability, nor does it consider potential impacts of spatial variability on crop response to water. This may result in both excess and deficits in water availability as well a reduced economic return (King et al., 2006). In southern Alberta, the necessity of using more precise and efficient methods of irrigation is increasing, but the adoption of such technology varies greatly with substantial room for improvement (Bjornlund et al., 2009).

Variations in crop yield can be greatly affected by spatial and temporal variations in the physical and chemical properties of soil combined with topographic variability (Yari et al., 2020). Understanding the distribution of these variations is an important factor in implementing precision irrigation. Soil variability is a result of different processes acting and interacting across a range of spatial and temporal scales, and frequently show spatial dependency (Cambardella et. al. 1994). Spatial and temporal variability in irrigated fields often results in uneven soil water retention and uptake by the crop (Xiang et al., 2007). This often results in dryer conditions in the high elevation areas, and ponding in the areas of lower elevation (Yari et al., 2020).

The use of precision irrigation involves deconstructing fields into smaller management zones based on identified characteristics that are similar within the zone and different among zones (Nicol, Nicol, 2021). These management zones can be created to define areas of a field with similar water requirements to improve crop productivity and water use efficiency (Yari et al., 2020). The variation across the field that is delineated by zones can then be accounted for and water allocations determined accordingly. Ultimately using precision irrigation involves applying the correct amount of water, at the correct time, in the correct location (Nicol, Nicol, 2021). The use of site-specific water application can improve both water and energy consumption (Smith et al., 2011). Southern Alberta consists of highly variable topography and soil, as well as variable climate conditions which makes regulation of the water supply a priority (Agriculture and Rural Development, 2010).

The delineation of management zones using spatial variability of crop, topography and soil properties is important for precise management of crop production (Khan et al., 2020). Many studies have been done investigating the use of management zones. Redulla et al. (2002) studied how spatial variability of pH, nutrient availability, and soil texture affected potatoes. They found that soil texture had the strongest correlation with yield due to the differences in available water-holding capacity. Khan et al., (2020) did a study to quantify spatial patterns of variability in soil and potato properties in PEI. Management zones were created to help quantify patterns. They concluded that most parameters had strong spatial dependency and the use of management zones would decrease the cost of production while increasing farm profitability.

Using precision irrigation methods to match irrigation amounts to the specific needs of crops and soil conditions can optimize water use efficiency and improve crop water productivity (Levidow et al., 2014). Taking into consideration the in-field variability in soil properties, topography and any other factors, precision irrigation maximizes irrigation water usage efficiency by reducing runoff and reducing excess water applications while still meeting crop water requirements (Nicol et al., 2010). Irrigation applications are targeted to directly meet the crop needs in the root zone ensuring optimal water availability for transpiration (Khakbazan et al., 2017). The increased water use efficiency that can be achieved through the implementation of precision irrigation is encouraged to reduce water use, which will allow current water allocations to be stretched further (Bjornlund et al., 2009). Precision irrigation also enables the producer to have control over the spatial and temporal distribution of water, allowing farmers to manage irrigation schedules based on real-time data (Xiang et al., 2007). This helps mitigate the effects of water scarcity, drought conditions, and climate change patterns in southern Alberta (Paterson Earth & Water Consulting Ltd., 2015).

There are also challenges to the implementation of precision irrigation in southern Alberta. The equipment and technologies needed to precisely manage the application of irrigation water can be costly and present a significant barrier to some producers (Nicol et al., 2010). There is also a higher degree of knowledge and dedication needed to use technology like variable rate irrigation water application across fields, or models that guide irrigation scheduling decisions. Nicol et al., (2021) found that the adoption of precision technologies was positively related to age, and that adoption is not weighted towards advanced technologies. They also found that the high costs of precision equipment were a major factor in adoption rates of this technology. Overcoming these challenges requires education, outreach programs, and financial incentives to support farmers that want to adopt precision irrigation methods (Nicol et al., 2010).

There has been substantial research done in the past comparing crop response to water, however many of these studies have reported values of means across replications in space and use statistical designs to block any spatial influences present. Limited work has been done to evaluate the profitability of accounting for spatial and temporal variability in irrigation management (King et al., 2006). A study done by Watkins et al. (2002) evaluated the economic and environmental benefits of site-specific irrigation management and variable rate nitrogen for seed potatoes in Idaho, concluding that site specific irrigation water management was likely to be both economically and environmentally beneficial and more so than variable rate nitrogen. O'Shaughnessy et al., (2020) also found that plant and soil water sensing feedback using multiple thermal stress thresholds and watering levels for SSIM has the potential to produce optimal crop response for grain sorghum using soil water- and plant-sensing technologies. King et al. (2006) found a 4%-6% improvement in yields per unit of water applied using site specific irrigation at University of Idaho, Aberdeen Research and Extension Centre, Aberdeen, USA, compared with a traditional centre pivot irrigation system.

2.7.1 Precision irrigation of Potatoes in Southern Alberta

Potatoes are an important crop in southern Alberta, and precision irrigation has provided a promising approach to optimize water use efficiency and improve potato yield and quality. By utilizing sensor technologies such as soil moisture sensors and weather stations, producers can monitor and adjust irrigation schedules based on real-time data, ensuring that water is applied when and where it is needed most (Wang et al., 2015). This will allow producers to minimize wasted water, reduce the risk of overwatering or underwatering, and promote optimal plant growth and tuber development (King et al., 2006). Precision irrigation can also improve nutrient management in potato production. By integrating water and nutrient management strategies, producers can deliver water and fertilizer precisely to where it is needed which will improve nutrient uptake efficiency and minimize nutrient losses through leaching. This precision in nutrient application can result in improved plant health, higher yields, and better tuber quality (Cambouris et al., 2014).

A major challenge in implementing precision irrigation in potatoes is the need for accurate and reliable sensor technology to monitor soil moisture and other relevant parameters. The selection, calibration, and maintenance of these sensors can be complex, requiring technical expertise and regular calibration to ensure accurate data collection (Wang et al., 2015). Cost associated with implementing precision irrigation systems in potatoes is also a major factor. Precision irrigation requires investments in sensor technologies, controllers, data management systems, and irrigation equipment. The initial costs may be significant, and farmers need to carefully assess the economic feasibility and potential long-term benefits of adoption (Bjornlund et al., 2009).

2.8 WATER USE EFFICIENCY

Efficient use of water is essential to meet the demands of agricultural production in southern Alberta. Water use efficiency (WUE) is defined as the yield produced from a unit of land area per millimeter of water used. The amount of water used by crops varies based on soil factors, precipitation, crop canopy, and meteorological parameters. Precision irrigation aims to maximize WUE by optimizing the usage of available water originating from precipitation and irrigation water application (Efetha et al., 2011). By matching water application to crop water requirements and considering the ability of the soil to store and retain water, producers can minimize water losses due to evaporation, percolation and runoff which overall improves WUE (Harms & Konschuh, 2010), ultimately conserving water and contributing to sustainable agriculture.

WUE can be influenced by many soil factors such as texture and structure that influence soil water holding capacity and infiltration, and there are no universal formulas for predicting WUE that are soil specific (Harms, Konschuh 2010). The WUE can be calculated using various methods, and one of the simpler methods determines water use efficiency by dividing end yield by the cumulative water used by the crop arising from stored soil moisture, precipitation and irrigation water applied. Total potato yield in a designated area is measured by harvesting potatoes and weighing. The water consumed by the crop in that area is also determined, including contributions from both irrigation and rainfall. Potato yield is then divided by total water consumed for an estimation of WUE (Efetha et al., 2011).

2.9 CONCLUSION

Irrigation plays a crucial role in meeting the increasing global food demand and ensuring the future availability of water for agriculture. Improved irrigation technologies and management practices have resulted in higher water use efficiencies and increased crop yields, despite competition for water resources, uncertain future water supplies due to climate change, and increased input costs. The irrigation industry in southern Alberta contributes significantly to the provinces economy and provides the opportunity to grow crops such as potatoes that would not be able to be grown in this area otherwise. The potato industry relies heavily on irrigation to achieve high yields and maintain quality. The adoption of irrigation water management practices that account for soil and environmental variability will allow for greater precision in delivering the right amount of water when and where it is needed in potato fields. However, there is relatively little published information on the performance of precision irrigation in potato production in Canada. Research and ongoing efforts to improve water management practices through site-specific irrigation management in Alberta will be critical for sustainable agricultural production and water conservation in the future.

3 Effect of Soil Hydrological Conditions on Potato Yield in Southern Alberta

3.1 PREFACE

Potato yield can be influenced by many factors, particularly the hydrological conditions of the soil. This chapter investigates the factors influencing soil hydrological conditions such as topographical complexity, weather, and soil complexity to determine how the interaction between these variables affects potato yield. Understanding how these factors influence potato growth is important to determine effective irrigation management practices needed to achieve top potato yields and qualities.

3.2 ABSTRACT

Precision irrigation, in which water is applied at different times and rates across and within farm fields according to environmental and soil conditions, is a promising solution for effective water resource management. By understanding soil and topography variations, appropriate irrigation management can be implemented to enhance irrigation efficiency, and crop yield. To assess these influences, a study was conducted from 2019 to 2022 in southern Alberta on five grower-irrigated potato fields. Soil parameters including texture, organic matter content, topography, and moisture usage, were measured every year. Five to six monitoring points were selected to represent the variation within each field. Weather stations were installed at each site to measure weather factors and determine evapotranspiration. Soil moisture sensors were used at each site to collect soil moisture data throughout the season. After each season, tubers were hand-harvested for yield and quality. Topographic complexity had significant influences on soil moisture dynamics linked to potato yield. Soil moisture had the greatest effect during the tuber bulking stage, with a significant positive effect in the 0-35cm depth, and a significant negative effect in the 35-60 cm depth. The variation in growing degree days and soil complexity did not have a consistent significant effect but there was a trend observed towards a negative impact on yield. In 2021, a "heat dome" event impacted tuber formation, highlighting the susceptibility of potatoes to extreme weather events. Customized precision approaches to irrigation water application based on an assessment of soil factors, topography, and anticipated weather can improve potato yield while adapting to water scarcity issues in southern Alberta.

3.3 INTRODUCTION

Potatoes are an important specialty crop in Southern Alberta, contributing significantly to the region's agricultural industry and economy. The use of precision irrigation technology has shown the potential to increase yield while reducing water usage by up to 25% compared to traditional irrigation methods (Ahmad, Sharma, 2023). Precision irrigation involves the application of the required amount of water, at the correct time, and at the right location in the field, allowing producers to conserve water resources without subjecting the crop to water stress (Bwambale et al., 2022). Precision irrigation also allows spatial and temporal variability to be accounted for to optimize crop yield and quality (Zaman, 2023). Adjustments can be made to irrigation applications to account for the effect the spatial and temporal variations across the field have on hydrological conditions such as infiltration, water retention, and current soil moisture levels. As the use of innovative irrigation technology becomes available to better manage water resources, the use of precision irrigation has increased (Levidow et al., 2014). To achieve high yields in potatoes, it is believed that soil moisture levels must remain at 65% available moisture or greater, especially during tuber initiation and tuber bulking (Alberta Agriculture and Forestry, 2011). Insufficient available water can lead to water stress, stunted growth, and reduced tuber formation (Wagg et al., 2021), while areas with poor drainage may result in water accumulation and waterlogged conditions, increasing the risk of root diseases and reducing potato yield (Li et al., 2006; Satchithanantham et al., 2012; Shock, 2007). Efficient irrigation management is imperative to optimize potato yield and quality and allows the crop to utilize nitrogen more efficiently, further promoting optimal crop growth and development (Akkamis, Caliskan, 2023).

Climatic conditions are an important part of potato production. Potatoes are a temperature-sensitive crop, especially during sprouting, emergence, and leaf area development. When temperatures exceed 30 °C, tuber initiation and development can be inhibited and result in physical damage to the tubers (Adekanmbi et al., 2023). Temperature is a determining factor for the growth and development processes of potatoes (Cao & Tibbitts, 1994). A certain amount of accumulated heat (growing degree days or GDD) is required for potatoes to complete their life cycle. The GDD quantifies the accumulation of heat units over a specified period, typically in relation to the growth and development of plants over a specific time frame, such as a growing season, and depending on variety require between 794-1,677 GDD to complete tuber bulking (Rodríguez et al., 2016). Sunlight availability is also very important for photosynthesis, promoting vigorous plant growth, carbohydrate accumulation in tubers, and overall crop productivity (Reddy et al., 2010). The combination of these weather-related factors directly impacts the success and productivity of potato crops.

Several studies have been conducted that have found significant within-field variations in soil and topography that affect potato yield and quality (Perron et al., 2018; Zare et al., 2019). Soil texture and structure are particularly important. Sandy soils with low water-holding capacity drain quickly, and store less water, leading to faster moisture depletion and increased water stress for potato plants. In contrast, clay soils with poor drainage can retain excess water, increasing disease risk, causing waterlogged soils, and impeding root growth and nutrient uptake (Zebarth et al., 2022). Achieving the optimum balance between soil moisture retention and drainage is essential for providing conditions that sustain healthy potato growth and optimize yield potential. The characteristics and features of the landscape have also been shown to have a significant impact on the various aspects of potato yield and quality in agricultural systems (Zebarth et al., 2022). Sloping or undulating terrain can impact the movement of water, leading to variations in soil moisture distribution (Appels et al., 2016). Areas with variable topography can experience water runoff, varied infiltration rates, and ponding (Appels et al., 2016; Li et al., 2006), causing water stress in plants and uneven soil moisture levels. By understanding the effects of soil properties and topography on water availability, producers can implement appropriate irrigation management practices to address resulting issues, thereby optimizing potato yield and quality.

The research presented in this chapter highlights the advantages of precision irrigation on potato yield. Specifically, it aims to answer the following research question: *How do soil hydrological conditions, topography, weather, and soil characteristics affect the yield of potatoes?* This study presents an analysis of the impact of precision irrigation on crop yield. It evaluates the influence of key factors such as soil, weather conditions, soil moisture, and topography on the cultivated crop's marketable yield. Based on the research question, the hypothesis proposes that variations in soil hydrological conditions within and among irrigated potato fields have a significant impact on potato yield. The findings of this study will help guide the implementation of precision irrigation techniques, enabling farmers to optimize water use, reduce environmental impacts, and maintain high-quality potato yields in southern Alberta's agricultural systems.

3.4 MATERIALS AND METHODS

3.4.1 Site Selection

Five farms with low-pressure center pivot irrigation in southern Alberta were monitored during the growing seasons of 2019 through 2022. The same five fields could not be monitored each year due to rotation requirements. Fields with different levels of topographic variation but with the same variety of Russet Burbank processing potatoes were selected. Farms were selected to include fields covering the major weather, soil, and topographical regions of southern Alberta. In the final year of the study, only four fields were available as one of the farms switched to a different variety of potatoes. Therefore, the study included nineteen unique field site years (Fig. 3.1). By working with the same farms during the four years of the study, factors such as land preparation, tillage, nutrient, and chemical management were implicitly considered.

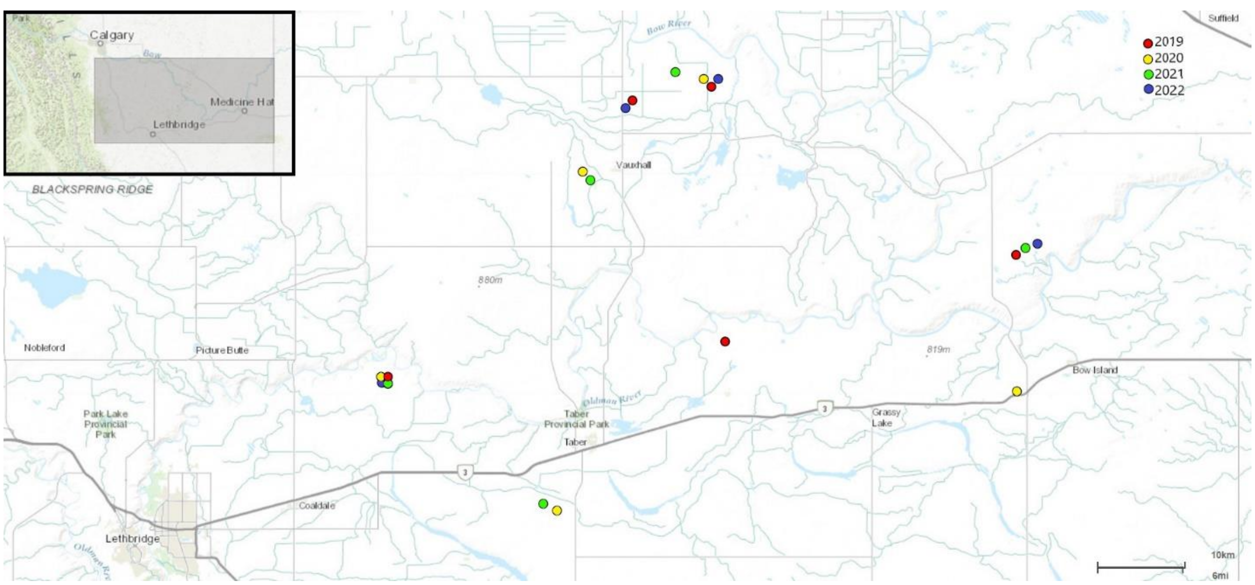


Fig. 3.1 The 19 field site locations of the five growers used in the study over six years in the study of precision irrigation of potatoes in southern Alberta. The field sites in each of the different years are mapped, showing the distribution of fields monitored, and on the top left, the general project location.

In each field, five (2019-2021) to six (2022) sites were selected for continuous soil moisture monitoring representing the different characteristics within the field. To select monitoring sites, first, the topography of the field was investigated using digital elevation models to assess key topographic attributes. The Alberta Soil Information Viewer (AGRASID) was used to assess soil properties, providing general information on soil type and classification, soil suitability and limitations, hydrological characteristics, and land capability and limitations. Using soil and topography data for each field, monitoring sites in each field were then chosen to cover each major region of soil texture, soil depth, and landscape position.

3.4.2 Data Collection

Once sites were selected, equipment was installed to measure moisture and weather conditions. Installation of monitoring devices occurred between late May to early June each year, and equipment was removed before harvest between late August to early September each year. Installation and removal dates varied each year depending on factors such as hilling, weather, field harvest, and other factors. Sites were visited weekly to gather data and observe field conditions, including taking photos of each monitoring point. Volumetric water content (VWC) and weather data were downloaded weekly, and the monitoring equipment was cleaned, maintained, and repaired as necessary.

3.4.2.1 Soil Moisture

Soil moisture was monitored using both soil moisture sensors as well as gravimetric samples collected regularly throughout the season. Multiple methods for soil moisture monitoring allowed for the validation of data.

Gravimetric Water Content

Gravimetric water content (GWC) samples were collected monthly from each monitoring location in the field to a depth of 1m in 20cm increments. After collection, soil samples were weighed wet, placed in an oven to dry for 24 hr at 105 °C, and then weighed once again. The gravimetric water content (g g^{-1}) was then calculated using equation 1.

$$\mathrm{GWC} = \frac{\mathrm{W}_w - \mathrm{W}_d}{\mathrm{W}_d} \mathrm{x}\ 100 \qquad [1]$$

Where GWC is gravimetric water content (%), W_w is the wet weight of the soil sample (g) and Wd is the dry weight of the soil sample (g). GWC was then converted to VWC by using Equation 2:

$$\mathrm{VWC} = \frac{\mathrm{GWC\ x\ BDs}}{\mathrm{BDw}} \qquad [2]$$

Where VWC is volumetric water content (%), BDs is bulk density of the soil sample (g/cm^3), and BDw is the bulk density of water (g/cm^3).

Volumetric Water Content

Soil moisture sensors were used at each site to continuously measure moisture levels in real time at various depths within the soil profile. The pre-determined sites were located by GPS. Four 10HS sensors (Meter Group Inc.) were placed at each location at 5cm, 20 cm, 35 cm, and 50 cm depths (Fig. 3.2) to collect moisture data within the upper potato-hilled region as well as below and set to collect data every 5 minutes using a Hobo H21 data logger micro station (Onset Computer Corporation).

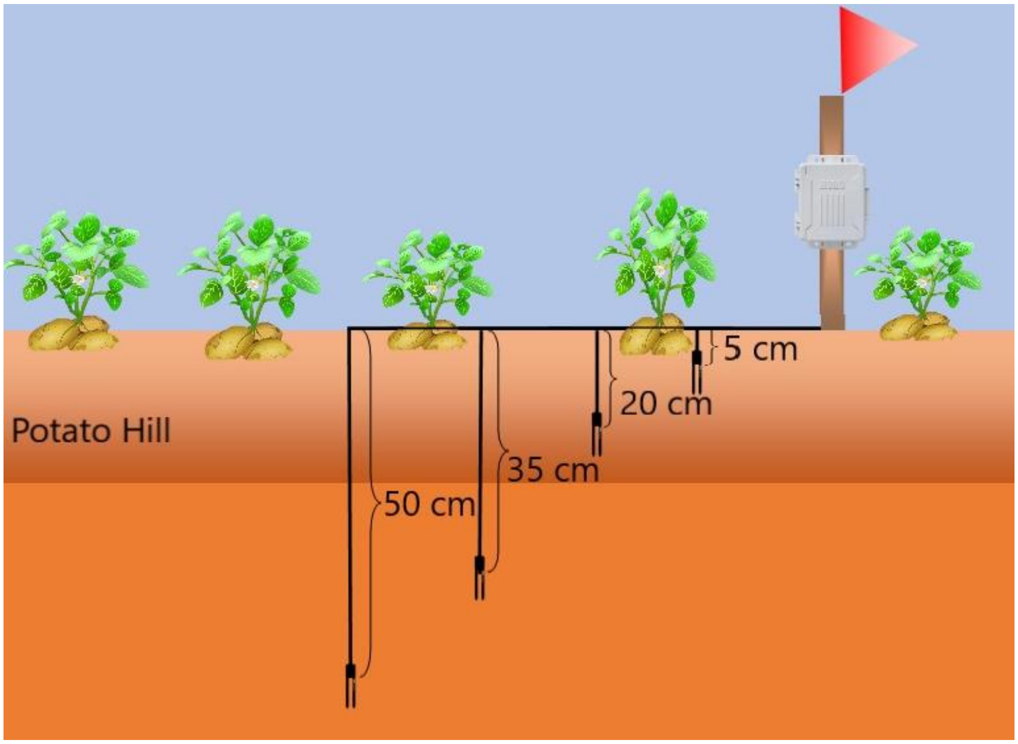


Fig. 3.2 Locations of soil water sampling probes in the soil profile. At each point, 10HS sensors were installed vertically in the soil at 5cm and 20 cm depths in the disturbed potato hill portion of the soil profile and at 35cm and 50 cm depths located below the potato hilling depth. Data was collected every 5 minutes using a Hobo H21 Data logger.

3.4.2.2 Weather data

A weather station was installed in a non-irrigated corner of each field. Each weather station used a Hobo H21 data logger micro station (Onset Computer Corporation), a tipping bucket rain gauge, an anemometer to measure wind speed/direction, a pyranometer to measure solar radiation, and a thermometer & relative humidity sensor. Sensors were mounted on a tripod (Fig. 3.3) and set to collect data in 5-minute intervals.

Fig. 3.3 Weather station installed in a non-irrigated corner of a Coaldale AB irrigated potato field in 2022.

3.4.2.3 Harvest

At the end of each growing season, three subplots were hand-harvested at each site. Harvest was done before the full field harvest and occurred between the last week of August and the first two weeks of September each year of the study. Three rows were selected at each site to harvest for total yield. From each of these rows, a 3m section was marked and tubers were dug and collected in mesh bags and labeled individually as replicates 1-3. An additional row of approximately 1m was hand-harvested from each site and 25 mid-size tubers between 113 and 284 g were selected and bagged separately for internal quality analysis.

3.4.3 Crop and Soil Analysis

3.4.3.1 Yield and Quality Analysis

For each replicate of potato tubers harvested, the number and weight of tubers were determined by weight class. Weight classes were 0-113g, 113-170g, 170-284g, 284-396g, and 396 g+.

Deformed/misshapen tubers were weighed separately, as were tubers damaged during harvest. Total yields for each replicate were calculated by adding all the weight classes together. Yield was first calculated as kg/m^2, based on a plot size of 0.91m (36 in) by 3m (118 in). This plot size represented the 3m sections that were hand-harvested, and the 0.91m (36 in) row spacing between potato hills.

One subsample of non-damaged tubers was taken from each replicate sample after weighing to determine the frequency of external and internal defects such as hollow heart, brown center, vascular discolor, flesh color, scab, and scurf. Tubers selected were 113g or greater in weight, were cut in half along their longest axis, and arranged with half in a 5x5 grid with the flesh facing upward, and the other half in a 5x5 grid with the flesh facing downwards to grade for internal and external defects (Fig. 3.4).

Fig. 3.4 Analysis of potatoes for internal and external defects performed by cutting 25 tubers in half and laying them flat on a table to observe defects.

The percent dry matter in the potato sample was determined by cutting blocks of unaffected flesh approximately 2.5-5 cm in width from 10 of the tuber halves from the previous subset. Samples were weighed fresh, then oven dried for 72 hr at 55 °C, then weighed once more. Dry matter was calculated using equation 3:

$$\%DM = \frac{DW}{FW} * 100 \qquad [3]$$

Where DM is Dry matter content (%), DW is Dry weight (g), and FW is Fresh weight (g).

Another subsample of 25 tubers was brought to a commercial lab (Independent Crop Inputs Inc.) immediately following harvest for analysis of specific gravity, sucrose, and glucose.

3.4.3.2 Soil Analysis

Soil texture was determined using particle size analysis with the hydrometer method (Gee and Bauder, 1986). In 2019, texture samples were collected based on the identification of soil horizons to a depth of 100 cm. From 2020-2022, rather than sampling by horizon, samples were collected at 10 cm depths and a textural analysis was completed for each depth. This allowed for more detailed and consistent sampling than the original method.

With medium to fine textured soils, 75g of oven dry soil (passing a 2 mm sieve) was weighed and placed into a dispersion cup. For coarse textured soils, approximately 100g was used. Then 100 mL of 5% Calgon (sodium hexametaphosphate) solution was then added as a dispersing agent, as well as water, then mixed with a stirring apparatus for 5 minutes. Solution was then added to a 1000ml cylinder, and water was added to bring the solution up to the 1000ml level. Cylinders were sealed with a rubber stopper, and completely inverted then brought upright until soil was completely dispersed throughout the solution. The cylinder was then placed on the table, the hydrometer placed in the solution and the first hydrometer and temperature readings were taken at 15 seconds, 30 seconds, one minute, four minutes and 60 minutes after inversion stopped. Subsequent readings were taken without disturbing the solution at 4 hours, then again at 24 hrs. Readings were also corrected for meniscus, Calgon, and temperature effects.

3.4.3.3 Soil and Topography Complexity

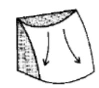
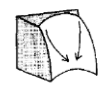
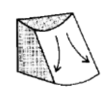
The more complex a field is in terms of the presence and distribution of various soil textural classes and landscape elements such as hills, depressions, and straight or curved slopes, the more difficult it can be to manage soil moisture. Soil complexity was determined for each field by calculating the Shannon entropy using equation 4:

$$Entropy = -\sum_{i} p(i) * \log_2\big(p(i)\big) \qquad [4]$$

Where p is the probability of occurrence for each distinct soil classification within the dataset (i). The Shannon's entropy index measures the degree of uncertainty, or entropy, associated with assigning a randomly selected individual to one of the predefined categories. The highest entropy value is achieved when all categories in the dataset have equal abundance, resulting in an entropy value equal to the natural logarithm of the number of classes. As the class sizes become more unequal, the weighted geometric mean of the p(i) values increases, leading to a smaller corresponding entropy value. In practical terms, when all abundance is concentrated in a single class, and other classes are extremely rare, Shannon's entropy approaches zero (Vacek et al. 2020). Soil complexity was calculated for each individual site and each individual field based on the distribution of soil textural classes in 10 cm increments of the 1 m deep soil profile.

Prior to each growing season, a topographical analysis of each field was performed, and a complexity rating was calculated based on an analysis of landforms observed in each field. This analysis included a geospatial approach using ArcGIS that integrated LiDAR-derived Digital Elevation Models (DEM) using high-resolution (15m) post spacing, 0.30 m vertical accuracy, and 0.50 m horizontal accuracy (Altalis Ltd.). From the DEM maps of slope flow accumulation, aspect, landform, and profile curvature were developed. The landscape element classification was then done based on the Pennock et al. (1987) method which combines the landform elements based on gradient, plan, and profile curvature. Classification criteria used for landform elements are outlined in Table 3.1. A gradient of <1° differentiated level elements from the other classes. The distribution of these landform elements in a hillslope system was depicted, considering water movement and distribution. Additional subclassification for linear plan curvature using a value of ±0.05°/m was utilized for further delineation when needed. Gradient and curvature thresholds were changed from the original method to match the low variability in the landscapes used in this study.

Table 3.1 Classification criteria for landform elements (Pennock et al., 1987) with threshold values adjusted to the southern Alberta landscape.

Profile Curvature (°/m)	**Gradient (°)**	**Plan (or planform) (°/m)**	**Landform**	**Element**	**Contour**	**Visual**	**Classification (code)**	**Classification (numeral)**
		Convex >0.0	Divergent	Footslope			DFS	1
Concave <-0.05		Concave <0.0	Convergent	Footslope			CFS	2
		Convex >0.0	Divergent	Shoulder			DSH	3
Convex >0.05		Concave <0.0	Convergent	Shoulder			CSH	4
Linear <-0.05 >0.05	High >1.0	Concave <0.0	Convergent	Backslopes			CBS	5
		Convex >0.0	Divergent	Backslopes			DBS	6
	Low <1.0		Level				L	7

The LiDAR data was used to create a detailed terrain map for each field, using Nowosad and Stepinski's (2019) method to create a quantitative ordering and classification of landscape patterns. This method uses bivariate random variables (x, y) to represent adjacent cell pairs that belong to different landscape classes, where *x* is a class of the focus cell and *y* is a class of an adjacent cell. A co-occurrence matrix is calculated using probability distributions of x and y, which shows how often different landscape classes appear next to each other. Joint entropy (H (x, y)) can then be calculated using these probability distributions, which reflect the complexity of the pattern. The analysis then evaluates the marginal entropy (H(y)) and the relative mutual information (U), to place complexities into a category. The landscape entropy values cannot be created for the site scale, so to link landscape complexity to site yields and site soil moisture dynamics we used a numerical classification of landform as outlined in Table 3.1.

3.4.3.4 Weather Analysis

Data was collected from weather stations on each field from 2019-2022. Daily potential evapotranspiration was calculated using humidity, temperature, wind speed and direction, and solar radiation using the Penman Monteith method (Allen et al., 1998), equation 5:

$$ET_0 = \frac{(0.408\,\Delta(\mathrm{R}_n - \mathrm{G}) + \gamma(900\,/\,(\mathrm{T}+273))\mathrm{u}_2(\mathrm{e}_{sat} - e_{act}))}{(\Delta + \gamma(1 + 0.34\mathrm{u}_2))} \qquad [5]$$

where ET_0 is the reference evapotranspiration (mm day^{-1}), Δ is the slope of the vapor pressure curve (kPa $°C^{-1}$), R_n is the net radiation (MJ m^{-2} day^{-1}), G is the soil heat flux(MJ m^{-2} day^{-1}) which is usually assumed to be zero, T is the mean daily air temperature at 2m (°C), u_2 is the wind speed at 2 meters (m s^{-1}), (e_{sat} - e_{act}) represents the vapour pressure deficit between saturated and actual vapor pressures of the air (kPa), and γ which is the psychrometric constant (kPa $°C^{-1}$). Once daily ET values were calculated, cumulative ET values were also calculated from June 1 through August 31 of each year.

Growing Degree Days (GDD) were calculated using measured temperature data to quantify the accumulated heat units at each location from June 1-August 31 each year. The calculation involves comparing the daily average temperature to a specific base temperature, as shown in equation 6.

$$GDD = \left(\frac{Tmax+Tmin}{2}\right) - Tbase \qquad [6]$$

Where GDD is growing degree days (°C), Tmax is the daily maximum temperature (°C), the Tmin is the daily minimum temperature (°C), and Tbase is the base temperature which is minimum temperature required for plant growth. A base temperature value of 7°C was used for this calculation for potatoes.

If the average temperature exceeds the base temperature, the difference is considered as the GDD for that day. However, if the average temperature is below the base temperature, the GDD value is set to zero. The GDD values for consecutive days are then summed to obtain the cumulative heat units over from June 1 through August 31 of each growing year. This is represented by equation 7:

$$GDDc = \sum \max(GDDi, 0) \qquad [7]$$

Where GDDc is cumulative GDD (°C), and GDDi is individual GDD values (°C).

3.4.3.5 Percentage Available Moisture

Soil texture data was utilized from each site to determine water holding capacity. Field capacity (FC) and wilting point (WP) for the 0-35cm root zone, and the 35-60cm root zone were determined in a two-step process. First, the average % sand, silt, and clay of each soil layer were entered into the pedotransfer module of SPAW Hydrology 6.0 software (USDA, 2023) to get a base value for FC and WP. This software estimates soil water tension based on texture and organic matter, with adjustments for density, gravel, and salinity using a set of empirical equations (Rawls et al., 1982; 1992; 1998; Saxton et al., 1986). These equations work well for a range of soil textures (0-60% clay and 0-95% sand). Due to the high spatial and temporal variability in the hydraulic properties of soils, the lack of representation for soil structure, and other limiting factors, it was necessary to adjust these estimated values based on field soil moisture observations at each monitoring site. The estimated field capacity values were compared to the VWC data collected from the average of the upper two moisture sensors, and the lower two sensors averaged, the GWC values converted to VWC as well as any field observations concerning soil moisture for validation. Graphs of the VWC values showed patterns where the soil moisture would move to the next lower profile, indicating that the layer was near field capacity. Where this level was different from the base FC values, values were adjusted to coordinate with field observations.

Once the level for FC and WP were established, VWC data was converted to available moisture (AM). Available moisture is a tool often used by producers as they are doing hand-feel verifications of their soil moisture throughout the growing season to monitor their moisture levels. Percentage available moisture is a function of soil texture, and water holding capacity. Where VWC measures the volume of liquid per volume of soil, available moisture will indicate that level as a percentage within the range between permanent wilting point and field capacity. The ideal AM range for potato production within the rooting zone is 65-100% available moisture (AF, 2016). This will ensure the crop has adequate moisture to meet crop needs throughout the growing season. Monitoring soil moisture in different fields based on AM was chosen because AM relates to the portion of water available for plant uptake, providing a more relevant comparison to adjust for the different soil properties. AM was calculated using equation 8:

$$AM = \frac{VWC - WP}{FC - WP} * 100 \qquad [8]$$

Where AM is available moisture expressed as a percentage between 0 and 100, FC is field capacity, WP is wilting point and VWC is volumetric water content, all expressed as a decimal fraction.

3.4.3.6 Statistical Analysis

The dataset generated from this project underwent analysis utilizing linear mixed-effects models in RStudio (version 4.1.1) (RStudio Team, 2021), which encompasses the R statistical software (version 4.1.1) (R Core Team, 2021) for fundamental computations. Within this software environment, supplementary packages were installed to facilitate comprehensive analysis. These included lme4, offering functions for fitting and scrutinizing mixed models; lmerTest, which provides p-values through type I, II, or III ANOVA and summary tables for linear mixed models. Soil entropy was calculated using Shannon entropy from the "entropy" package. This analysis aimed to explore the impacts of various factors—such as available moisture, growth stage, topographical complexity, weather conditions, and soil complexity—on both total harvested yield and total marketable yield. This study is observational, not experimental, so the usual treatment-control statistical analysis cannot be performed. Instead, we observed existing conditions, behaviors, or relationships in the field to gain insights into the predictors and their effects on potato yield during different growth stages and under varying available moisture conditions.

A mixed-effects model that accounts for the hierarchical and clustered nature of the data was used because with multiple factors at play, it was important to consider the distinct interactions between them and their impact on yield. Our analysis included factors such as weather conditions, soil moisture levels, topography types, and soil complexities. By utilizing a mixed-effects model, we were able to capture the unique characteristics of each field, accounting for the variability between different locations (random effects) and the impact on potato yields. This approach was necessary as there was no experimental design with controlled factors that could be analyzed with traditional linear regression or ANOVA. We used an aggregate of moisture data for the statistical analysis, averaging AM in the upper (0-35 cm) and lower (35-60cm) root zones during two stages: tuber initiation, occurring over a two-week period around 45 days after planting, and tuber bulking, which follows tuber initiation and lasts for approximately 60 days.

To facilitate analysis, the topography of each point was classified as either 'flat' (class 7) or 'non-flat' (classes 1-6). About half of the points were deemed 'flat,' and all points were thus grouped as 'flat' (ranked 7) or 'non-flat' (ranked 1-6). Soil entropy values were computed for each unique combination of site and year and GDDs were calculated for each monitoring season. Total overall yield was included as a variable, and 'marketable yield' was calculated by summing the tubers greater than 170g (6oz) to represent a slightly higher value of marketable tuber. Tubers over 113g (4oz) are purchased at processing facilities in southern Alberta, with premiums paid for more tubers over 170 g (6oz) (PGA, 2022). Initial investigations into relationships of internal and external quality parameters were not shown to affect yield and quality in this study, so the only quality parameter investigated in the final models was tuber size, indicated by the variable marketable yield.

The dataset included soil entropy, topographical entropy, growing degree days, and total yield as variables. We developed 8 final models (Table 3.2) based on available moisture and growth stages in two different depths of the soil profile. Random effects account for variations between fields, sites, and data collection points, while fixed effects evaluate the impact of independent variables on dependent variables.

Table 3.2 The eight linear mixed-effects models used for analyzing potato yield based on rooting depth, growth stage, and dependent variables. Fixed effects include AM, Topographical Entropy, Soil Entropy, and GDD, while random effects consider field, site, and point variations.

Model Name	**Rooting Depth**	**Growth Stage**	**Dependent Variable**	**Fixed Effects**	**Random Effects**
1	0-35cm	Tuber Initiation	Total Yield	AM, Topographical entropy, Soil Entropy, GDD	Field, Site, Point
2	0-35cm	Tuber Bulking	Total Yield	AM, Topographical entropy, Soil Entropy, GDD	Field, Site, Point
3	35-60cm	Tuber Initiation	Total Yield	AM, Topographical entropy, Soil Entropy, GDD	Field, Site, Point
4	35-60cm	Tuber Bulking	Total Yield	AM, Topographical entropy, Soil Entropy, GDD	Field, Site, Point
5	0-35cm	Tuber Initiation	Marketable Yield	AM, Topographical entropy, Soil Entropy, GDD	Field, Site, Point
6	0-35cm	Tuber Bulking	Marketable Yield	AM, Topographical entropy, Soil Entropy, GDD	Field, Site, Point
7	35-60cm	Tuber Initiation	Marketable Yield	AM, Topographical entropy, Soil Entropy, GDD	Field, Site, Point
8	35-60cm	Tuber Bulking	Marketable Yield	AM, Topographical entropy, Soil Entropy, GDD	Field, Site, Point

3.5 RESULTS AND DISCUSSION

3.5.1 In-Field Variability

This research conducted an analysis of in-field variability, including soil texture, soil complexity index, and topography complexity, to evaluate their impact on soil moisture dynamics affecting potato yield and quality.

Texture

The analysis showed a high degree of within-field variability in soil texture (sand, silt, and clay content) across the various sampled fields, with some fields exhibiting predominantly sandy soils, while others had higher proportions of silt and clay. Fig. 3.5 shows the texture classifications in the farm fields based on their proportions of sand, silt, and clay. Out of the 475 samples analyzed from 2019 to 2022, Loam was predominant, occurring 173 times in total. Clay Loam was observed 96 times, followed closely by Sandy Clay Loam at 92 instances, while 58 samples were classified as Sandy Loam. Silt Loam was found in only 19 samples, Clay texture was found in 16 samples, and Silty Clay Loam textures were found in 14 samples. Heavy Clay was only observed once, and Loamy Sand was detected only twice.

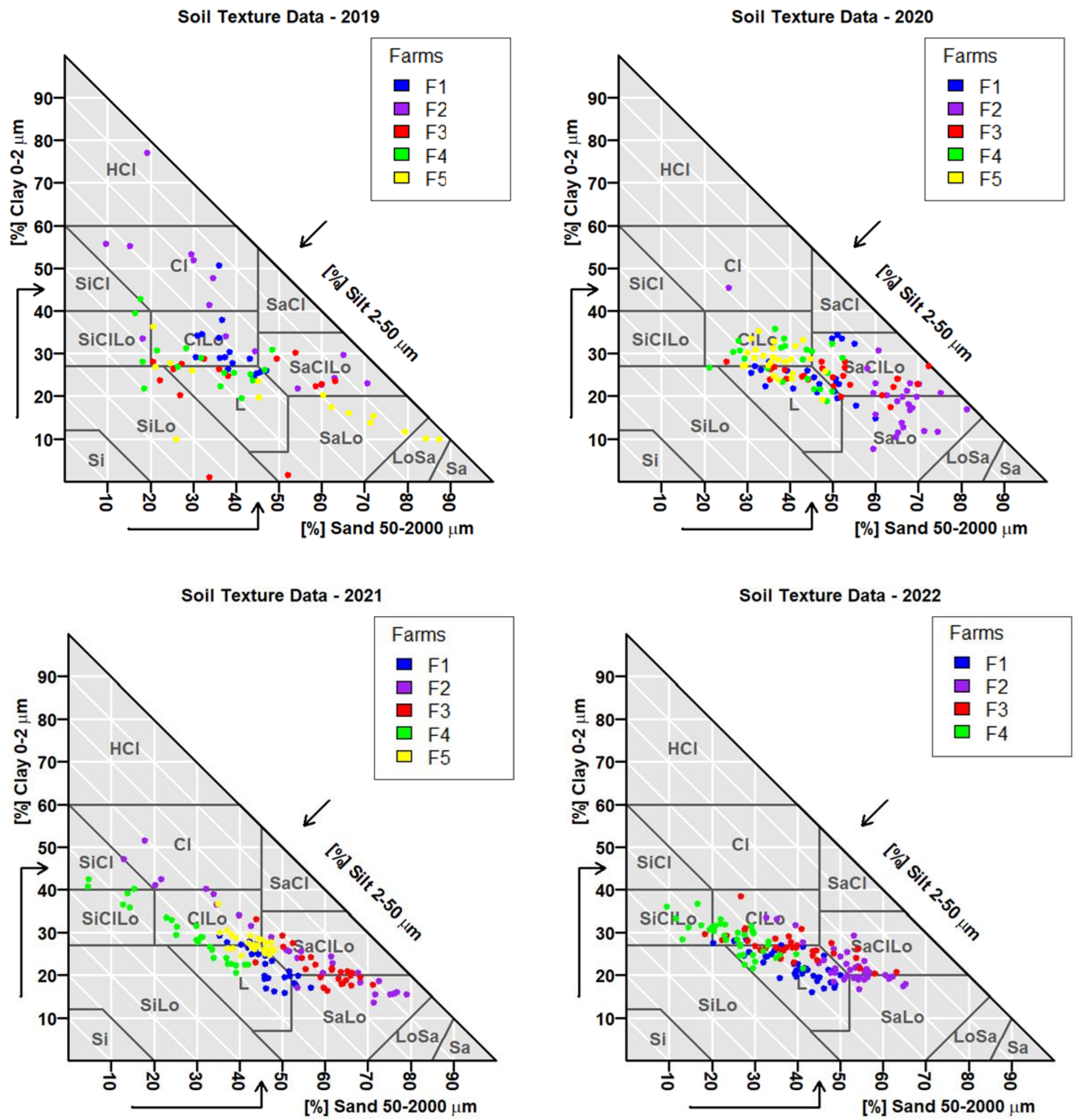


Fig. 3.5 Soil texture variability in the farm field sites studied during each respective year (2019-2022), separated according to farm name. The distribution of soil textures, including sand, silt, and clay, is represented in each soil texture triangle, with each point depicting samples taken at 10-cm intervals from each monitoring point in its respective field.

Soil and Topographic Complexity

The soil complexity index and topography complexity index, both functions of entropy, were analyzed across all sites over the four years of this study to assess the overall complexity based on the variability in soil properties and topographical features in each field. Differences in soil and topographical complexities over the years are shown in Fig. 3.6.

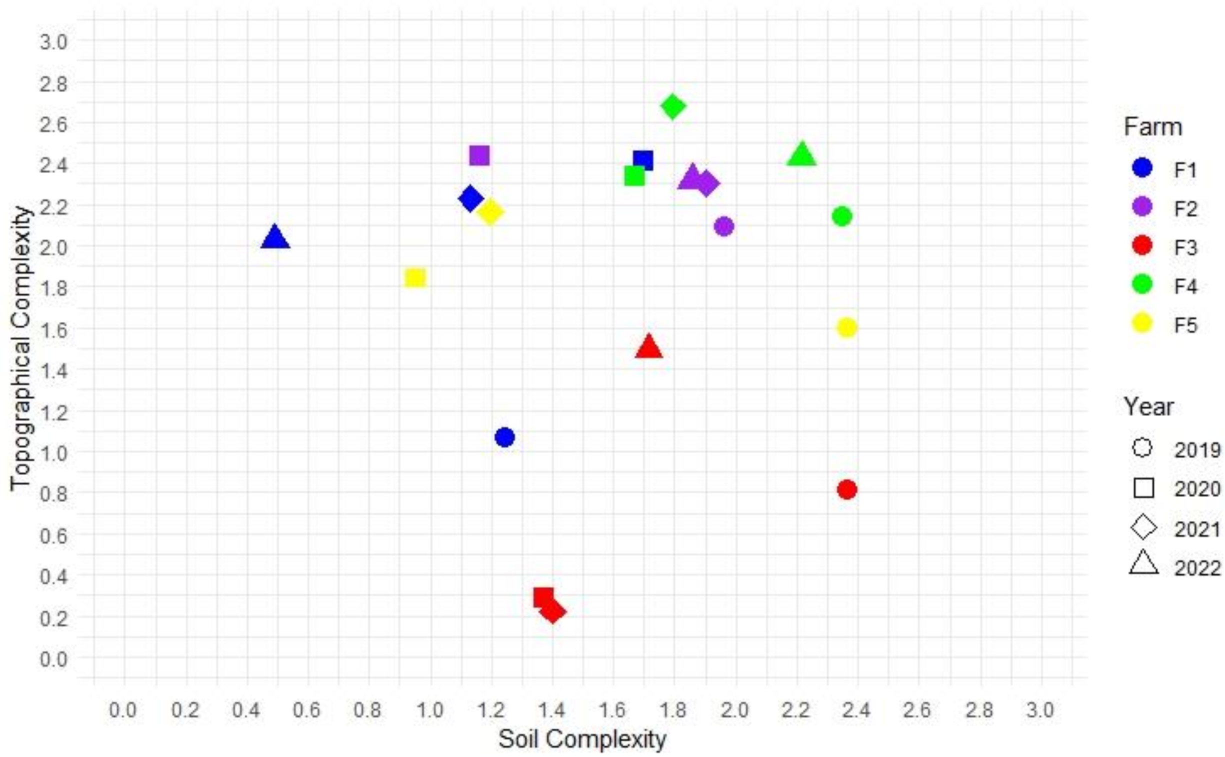


Fig. 3.6 Scatterplot displaying the relationship between Soil Complexity (on the x-axis) and Topographical Complexity (on the y-axis) for different sites (represented by different colors) and years (represented by different shapes). The data demonstrates the variations in soil and topographical complexity across fields investigated from 2019-2022.

The variability in both soil and topographical complexity between the different farms and years can be attributed to the change in field location each year due to rotational requirements. Overall, topographic and soil complexity in this study were not strongly linked. However, the F3 farm consistently had lower levels of topographical complexity among fields throughout the study period, regardless of fluctuations in soil complexity. This may reflect more uniformity in topography across the land base used in potato production on this farm. In contrast, the F4 farm shows substantial variations in both soil and topographical complexities, suggesting that many parameters and their interactions are likely controlling water relations and potato yield across and within fields on this farm.

A grower will need to consider differences that exist in the degree of soil and topographic complexity among each different field used for potato production on their farm and how this may influence requirements and potential returns on precision irrigation strategies implemented. Different elevations, surface curvature patterns, and associated soil properties often cause variability in yields, particularly in the later growth stages (Minda et al., 2019). The use of precision irrigation to account for different topographical positions and soil textures can potentially be of benefit. Using multivariate approaches to address the different challenges presented by field variability can allow producers to manage their irrigation more effectively (Zebarth et al., 2021).

3.5.2 Variation in Weather

Seasonal temperature statistics are shown in Table 3.3. The variability between years was larger than that within years between farms, which would be expected based on the distance between the farms being less than 100 km. The 2021 season was the warmest year, both in daily maximum and minimum temperatures, followed closely by 2022, while 2019 and 2020 had similar values that are close to the climate normal (data not shown).

Table 3.3 Average seasonal temperatures (°C) for the years 2019 to 2022, categorized by farm and temperature type (maximum, minimum, average).

	Temperature °C	**F1**	**F2**	**F3**	**F4**	**F5**
2019	Maximum	25.4	25.1	26.1	26.4	26.4
	Minimum	9.6	9.8	9.7	9.6	9.2
	Average	17.3	17.2	17.6	17.8	17.6
2020	Maximum	26.2	25.6	26.8	25.7	26.2
	Minimum	9.5	9.8	9.9	9.6	9.1
	Average	17.7	17.7	18.1	17.6	17.5
2021	Maximum	28.5	28.0	28.0	29.8	27.7
	Minimum	10.4	10.0	10.9	11.1	11.0
	Average	19.5	18.8	19.3	20.3	19.2
2022	Maximum	27.5	27.0	27.3	27.3	X
	Minimum	11.0	10.6	10.8	10.8	X
	Average	19.2	18.8	19.1	19.1	X

Differences in temperature patterns during the four years are also captured in the cumulative Growing Degree Days of the years and farms (Fig. 3.7). The 2021 season stood out due to the “heat dome” event that occurred during late June and July when temperatures rose to unseasonably high values of 35°C to 40°C in large parts of the region (data not shown).

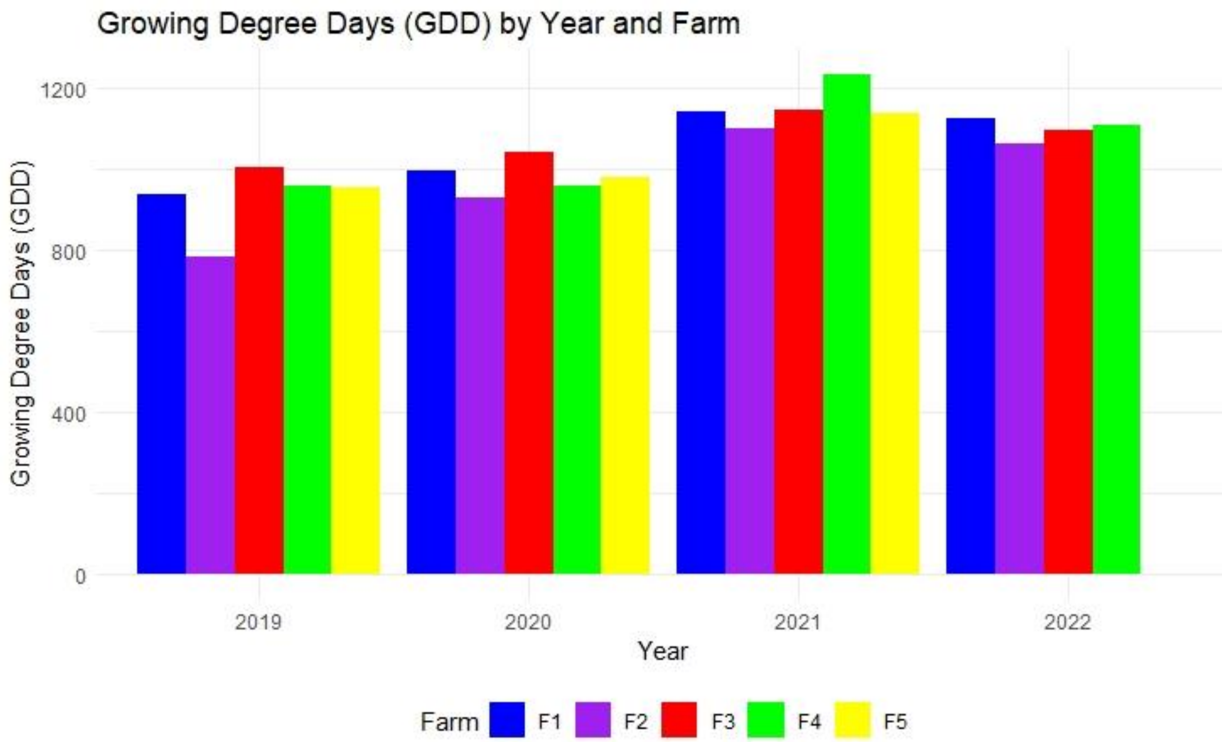


Fig. 3.7 Growing Degree Days (GDD) by year and farm. The bar chart illustrates the variation in Growing Degree Days (GDD) for each farm across the years 2019 to 2022.

Due to the summer heat dome event, 2021 featured 2-6 more days over 30°C and 7-12 more days over 35°C than 2022 (Table 3.4). Tang et al. (2018) found that exposing tubers to temperatures above 30°C resulted in reduced tuber formation and tuber mass, even though the plants showed no signs of stress. During tuber bulking, the effect of heat on tuber formation reduces as tubers become more developed (Kim, Lee, 2019). As the heat dome event occurred in the early growth stages of the potato crop, a negative impact on tuber formation was expected (see detailed results in Section 3.5.4).

Table 3.4 Number of days during each monitoring period in 2019-2022 where the maximum daily temperature was over 30°C and 35°C.

		F1	**F2**	**F3**	**F4**	**F5**
2019	Days over 30°C	13	12	19	20	22
	Days over 35°C	16	12	21	22	25
2020	Days over 30°C	24	20	24	17	21
	Days over 35°C	25	21	26	17	21
2021	Days over 30°C	32	32	31	33	26
	Days over 35°C	45	38	39	50	34
2022	Days over 30°C	29	26	29	30	X
	Days over 35°C	33	30	32	38	X

Climate normals for monthly rainfall in June, July, and August in the Lethbridge area are 83, 43, 37 mm, respectively, with considerable variation around the mean (Environment and Climate Change Canada, 2020). The spatial variability of rainfall is larger than that of temperature, therefore seasonal rainfall totals variation between farms was sometimes as large as that between years, especially in 2019 (Fig. 3.8). Averaged per year, 2021 was the driest, 2019 was dry to moderately wet, and 2020 and 2022 were near-normal.

Irrigation practices varied significantly among farms, highlighting the diverse water management strategies employed by agricultural producers. One would expect more irrigation water to be applied in a season when rainfall is low and temperature is high, and vice versa, but that relationship is not clear as shown in Fig. 3.8. Drier, hotter conditions in the “heat dome” of 2021 did not appear to result in a consistent increase in application of irrigation water on the farms compared to other years.

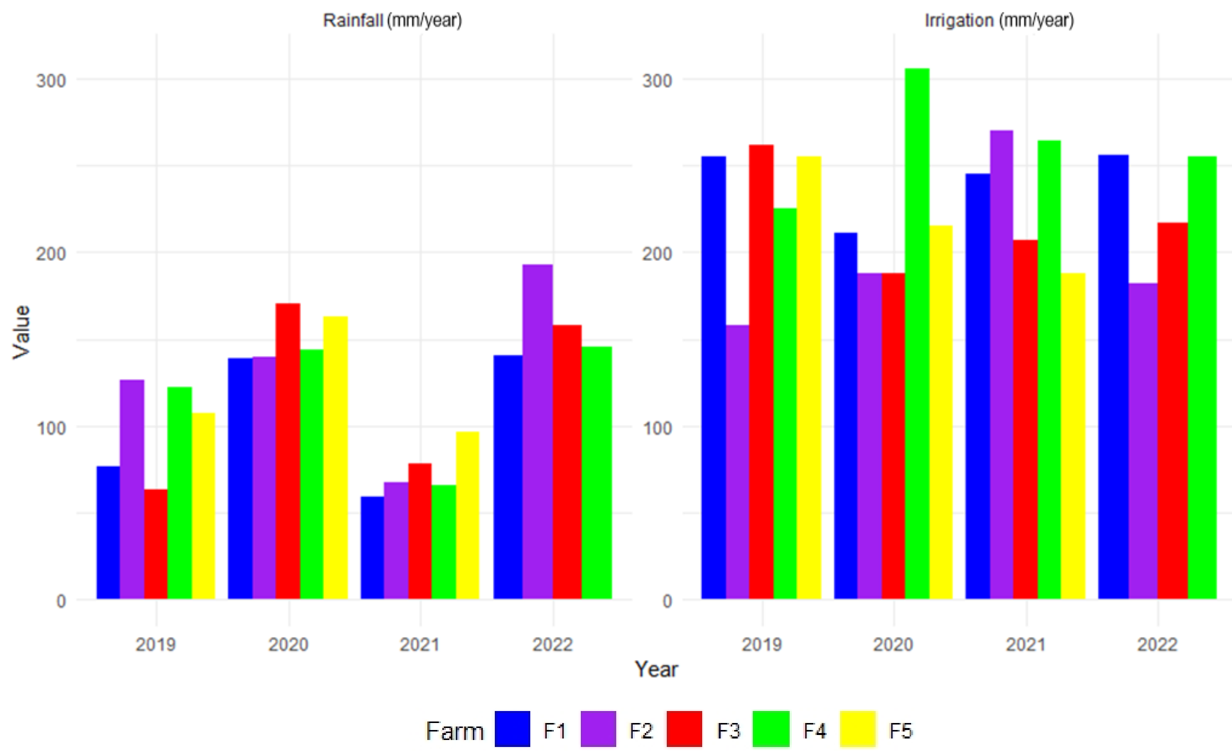


Fig. 3.8 Seasonal totals from June through August for rainfall and applied irrigation water at each site from 2019-2022.

The ET represents the total water loss due to both soil evaporation and plant transpiration, while precipitation indicates the total amount of water received through rainfall and irrigation in mm over the year (rain plus snow). The differences between ET and precipitation values indicate the net water loss or gain in each farm, impacting the water availability for crops. In Fig. 3.9, seasonal crop ET and seasonal precipitation are presented. This figure illustrates that the totals may also be compensating for ET differences between locations resulting from the small temperature differences, as well as the differences in lengths of the monitoring periods between farms and years. The fluctuations in ET levels highlight the diverse water demand and potential water stress experienced by the potato crops in different fields. The values shown in Fig. 3.9 indicate the average ET and precipitation or water input (rainfall plus irrigation) for each respective monitoring season (June through August). Average ET values for each season range from 267 mm to 342 mm, and total water input values ranges from 340 mm to 488 mm. These numbers suggest that farmers either over irrigated, or that timing of rainfall resulted in a positive water balance at the end of the monitoring periods. Corresponding soil moisture observations (Section 3.5.3), highlight how these fluctuations in water supply impact soil hydrological conditions during tuber initiation and tuber bulking, with variations observed at each site.

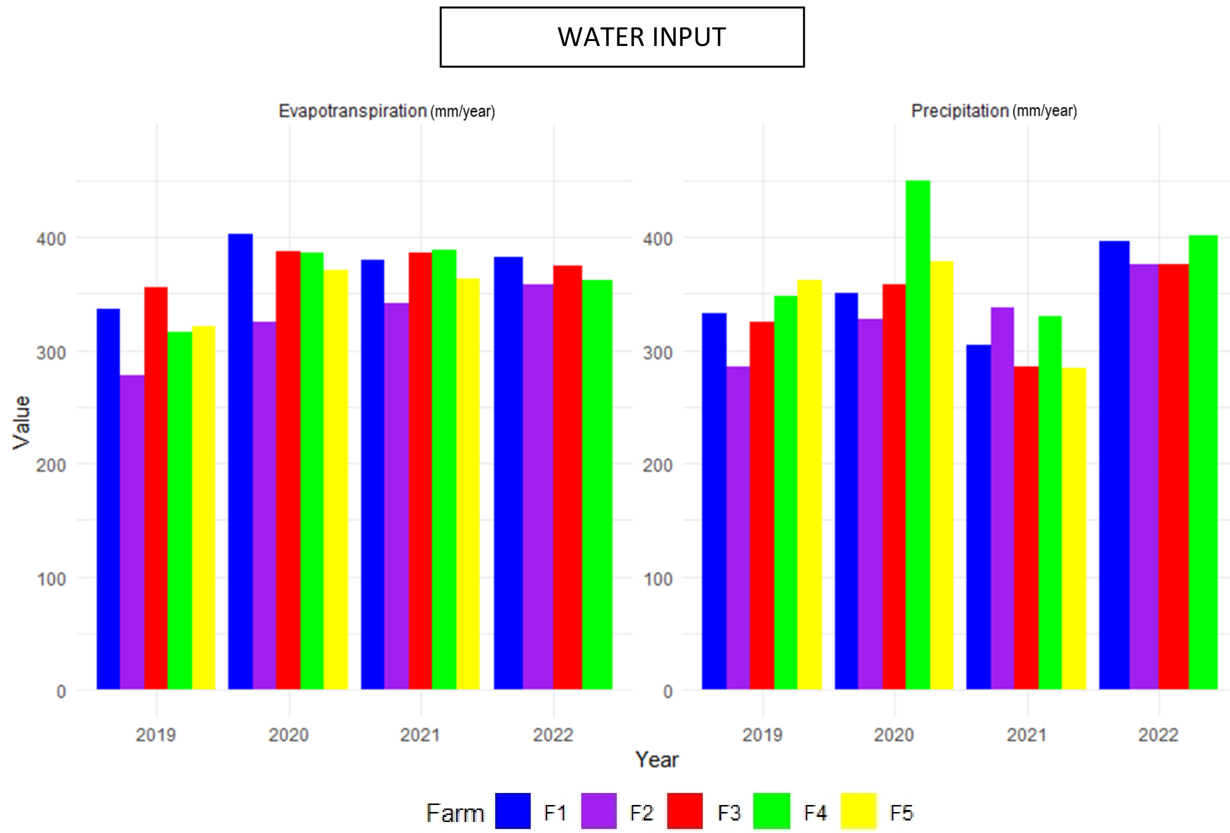


Fig. 3.9 Comparison of seasonal Evapotranspiration (ET) and Water Input (rainfall plus irrigation) (mm) for the different farms across the years (2019-2022).

Temperature, sunlight, and precipitation amounts during the growing season have been found to affect tuber growth and development, and ultimately yield and quality (Minda et al., 2019). A study done by Perron et al., (2018) found that tuber yield variability among years of their study was greatly influenced by weather during the growing season, which is like that observed in this study. When a water deficit is created by ET values exceeding total precipitation, it becomes necessary to add extra water in the form of irrigation to achieve maximum yields and qualities. A study done by Li et al. (2007), determined that water deficit has a significant effect on plant growth and tuber development. Other studies such as Bélanger et al., (2000), and Wagg et al. (2021), confirm this effect. In this study, rainfall values alone were not sufficient to provide adequate water to potato crops without a deficit occurring, therefore without additional water in the form of irrigation, the crops would not have received adequate moisture.

3.5.3 Variation in Soil Moisture

Soil AM levels varied over the season at all sites, because of water lost from ET and water added through rainfall and irrigation. The interaction between soil characteristics, weather, and topography resulted in additional variations among and within individual fields in the study. As an example, the available moisture for the F2 farm in 2022 at 6 different locations in the field is shown in Fig. 3.10. The variability in the 0-35 cm depth over the season was more pronounced due to the shallow water being used at a higher rate by the crop and lost due to evaporation, then replenished by irrigation and precipitation. The 35-60 cm depth was less variable in AM, with soil available moisture levels typically maintained within the desired 65-100% AM range. More variability is typical in the top 35 cm as opposed to the 35-60cm depth as potatoes extract 70% of their seasonal water from the top 30 cm, where roots are most prevalent and effective at removing water (AF, 2011). A study done by Starr et al. (2008), investigated potato water uptake within and below the hill. Their research found that the greatest uptake was found in the hill but was significantly less below the hill. Similarly, the highest uptake was generally in the shallower depths, decreasing consistently as depth increased. This is consistent with what we observed in this study, with the moisture levels varying more in the hill due to higher uptake and remaining more consistent below the hill.

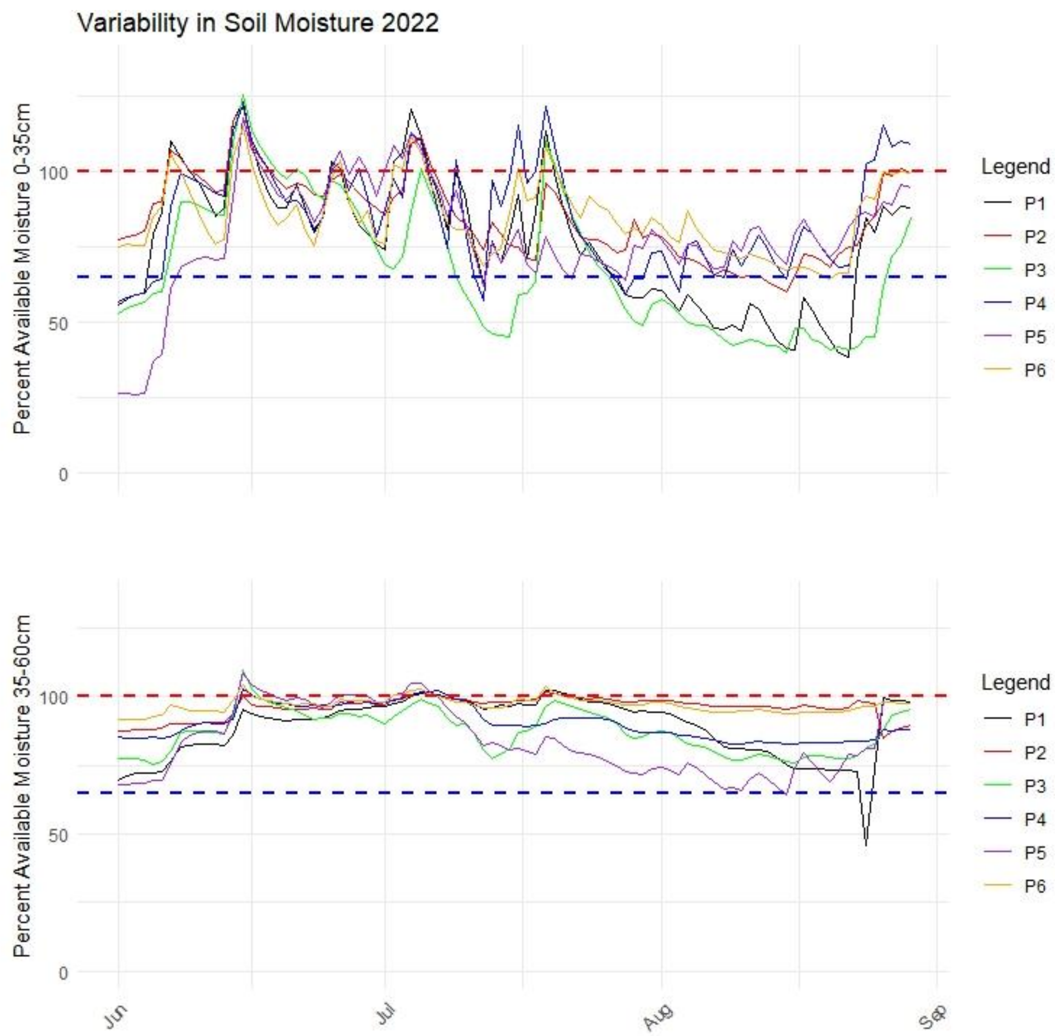


Fig. 3.10 Variation in percent available moisture (as calculated using equation 3.9) in the 0- 35cm and 35-60 cm depths of the rooting zone at the F2 farm 2022 site from June 1 through Aug 28, 2022. P1-P6 represent individual sites within the field. Dashed lines represent 100% AM or Field capacity(red) and the Irrigation Threshold of 65% AM (blue) respectively.

This study focused on available soil moisture over two important stages of potato growth: tuber initiation and tuber bulking. During these growth stages, the variability of available moisture levels at depths of 0-35 cm and 35-60 cm across farms and years were compared. The effect of external factors during these stages plays an important role in determining total yield and tuber size. As found by Taleb et al., (2022), tuber initiation and tuber bulking stages have the highest sensitivity to irrigation treatments compared to other stages, and to optimize yield and quality, irrigation must be carefully managed during these growth stages.

The coefficient of variation was calculated for AM during each growth stage, for each site, as shown in Table 3.5. The variation is consistently higher in the 0-35 cm depths, except for 2021 during tuber bulking, where the CV for the 35-60 cm depth was slightly higher due to an exceptionally hot, dry growing season. Data from 2019 show the highest level of variation overall, especially during tuber initiation in the 0-35cm depths. When comparing CV values across farms, most were comparable with average values between 9-11%, apart from the F1 farm, which was consistently less variable than the other farms. The values in this study are low in comparison to a study done in PEI by Khan et al. (2020)., who found soil moisture CV values that ranged from 15.1-34.5%, indicating much higher variation. A study by Star (2005), found soil moisture CV values of 16-30% and determined that the CV values for water content can be affected by many parameters, but are primarily affected by spatial variability, and random measurement error.

Table 3.5 Coefficient of Variation in percent for available moisture in the 0-35 cm and 35-60 cm depths of the rooting zone during the tuber bulking and tuber initiation stage.

		Coefficient of Variation (%)			
		Tuber Initiation		**Tuber Bulking**	
Year	**Farm**	**0-35 cm**	**35-60 cm**	**0-35 cm**	**35-60 cm**
2019	F1	1.9	3.7	7.8	3.5
	F2	13.4	11.0	5.1	5.2
	F3	20.2	8.1	5.7	7.0
	F4	33.0	17.2	11.7	7.1
	F5	20.1	11.1	22.4	18.4
2020	F1	16.7	1.4	7.0	9.5
	F2	19.3	6.2	25.0	12.3
	F3	14.1	4.7	7.7	13.6
	F4	16.0	3.9	7.6	2.6
	F5	11.0	7.6	8.7	4.3
2021	F1	10.6	4.0	7.6	8.9
	F2	8.3	6.7	12.1	15.4
	F3	23.8	10.7	1.0	3.0
	F4	3.4	3.4	9.9	9.9
	F5	7.6	17.1	7.4	4.3
2022	F1	11.6	4.0	9.0	7.7
	F2	9.6	3.9	13.4	5.5
	F3	7.9	9.5	2.3	5.4
	F4	12.9	12.9	12.1	18.4

During the initial growth phase of potatoes, the upper root zone (0-35cm) had many of the AM values in the ideal range of 65-100% (Data shown in Appendix). However, in 2019, median values were below the target AM in the 0-35 cm depth for F2, F3, and F4 farms. The water within the 35-60cm depth displayed less variability, with higher medians, where few values fell below the 65% AM target. Fig. 3.11 illustrates the variability in AM in the tuber bulking period which occurs in the last half of July and through most of August, in the 0-35 cm and 35-60 cm depths. Although there was variability from field to field, most AM values were generally within the desired range at both depths in all years except 2019. During the tuber bulking stage in 2019, the same three sites had median average soil moisture values below the target of 65% in the upper depth, similar to the tuber initiation stage. However, the majority of values in the 35-60 cm depth, remained above the 65% and had less variation than the 0-35cm depth. In addition, as the potatoes grow and approach maturity, the lower part of the soil profile contributes more water with increasing maturity which affects root zone variability during tuber bulking (AF, 2011). The trends and patterns between the two stages of growth were generally consistent. Sites that were drier during tuber initiation were typically drier during the tuber bulking stage.

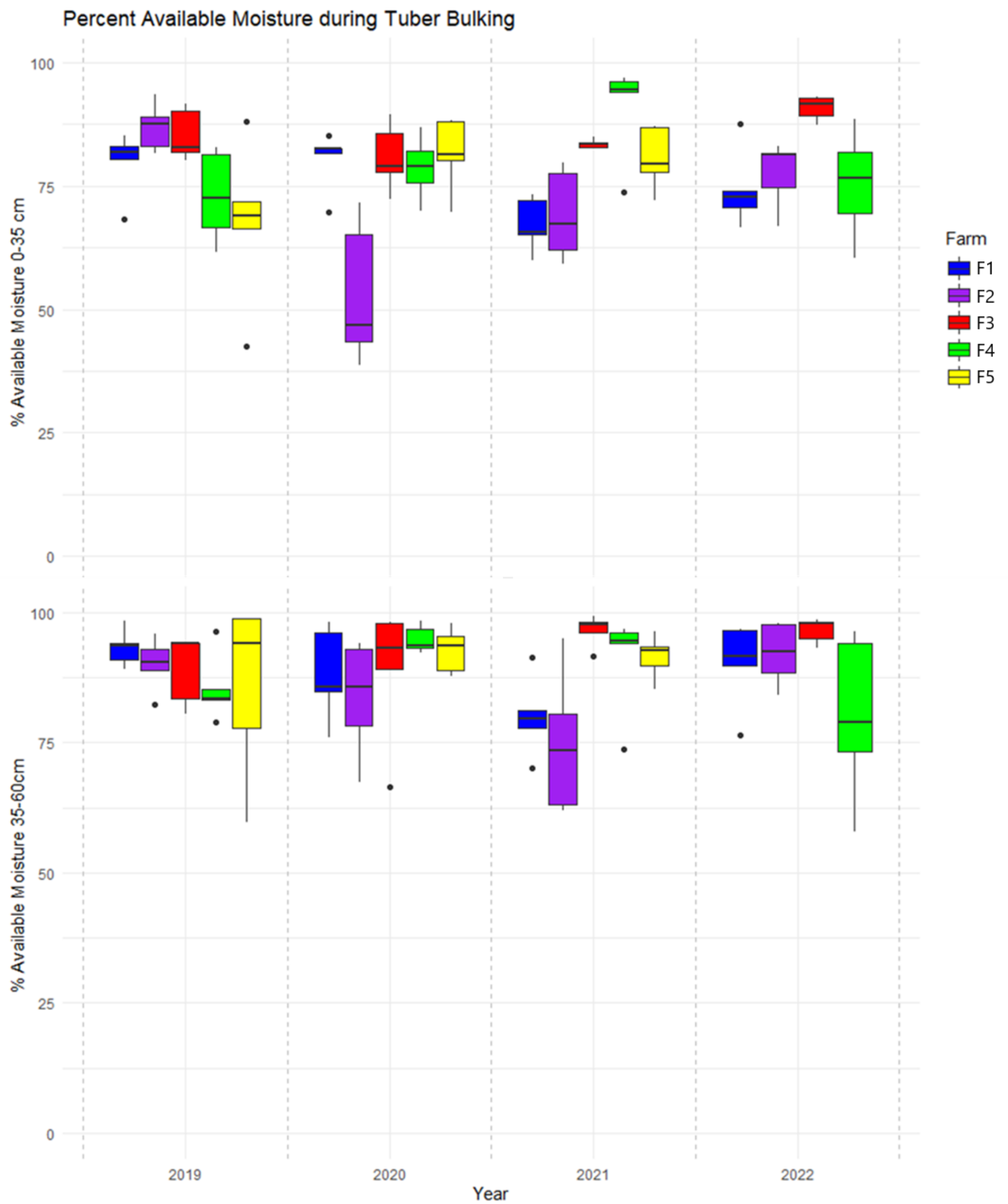


Fig. 3.11 Variation in percent available soil moisture in the 0-35cm and 35-60cm depths during the tuber bulking stage mid July to early August, from 2019-2022.

Soil moisture can be influenced by many factors such as ET, precipitation, irrigation, soil, and topography in potato production. A study by Martin et al. (1992) at Lincoln, New Zealand showed a strong linear relationship between soil moisture and yield of potatoes, with moisture deficits either before or during tuber bulking resulting in consistent yield reductions. However, in the study by Martin et al., they did not measure available soil profile moisture content continuously as in the present study. Understanding relationships among variables in detail and combining soil, plant, weather, and topography data in an irrigation management program can significantly improve water use efficiency and allow producers to optimize their irrigation monitoring and management practices (Zaman, 2023).

3.5.4 Variation in Yield

Potato yield can vary greatly within fields, among fields and sites, and across years due to numerous factors. A study done by Po et al. (2010), in Michigan USA, utilized 23 different predictor variables consisting of physical, chemical, and spectral variables for potato yield prediction. These variables were selected out of an original pool of 42 variables. The variables that affected yield were different between the different fields in their study, though soil properties and soil moisture produced the most marked impacts. Significant variation in yields were observed despite the use of best management practices due to all the variables influencing overall yield. In our study, properties such as soil composition, moisture levels, nutrient availability, and local microclimates were all likely contributors to variations within fields. External weather factors including temperature, rainfall, and growing degree days also impacted year-to-year yield variations. Fig. 3.12 shows the variation in marketable yield in tonnes per hectare, across all sites between 2019-2022.

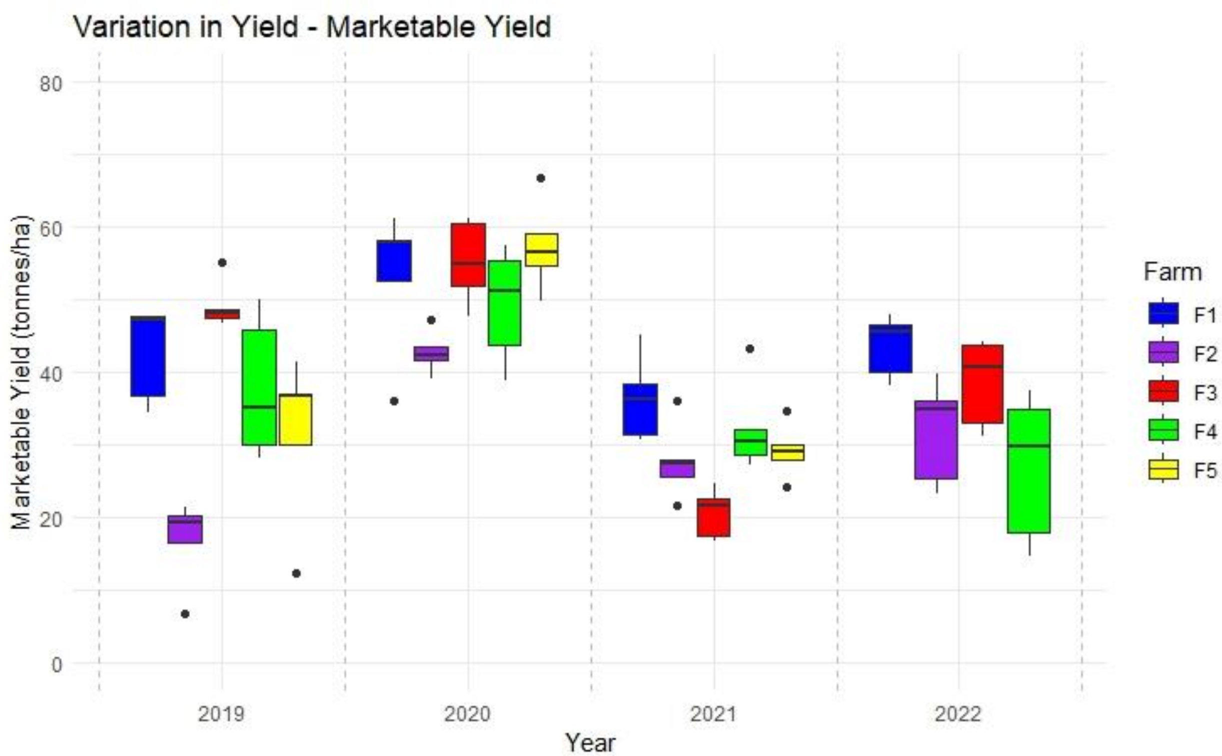


Fig. 3.12 Variation in marketable potato yield in tonnes per hectare for all farm sites between 2019-2022.

When all sites were averaged by year, 2019 had an overall total yield average of 49 tonnes/ha and a marketable yield average of 37 tonnes/ha, with considerable variability among sites. The provincial producer total average for that year was 40 tonnes/ha (AF, 2019-2022). In contrast, the year 2020 had the highest overall potato yields among all sites, with an average of 63.5 tonnes/ha total yield and 51.6 tonnes/ha marketable yield. However, the provincial average was lower at 38 tonnes/ha (AF, 2019-2022). The year 2021 showed the lowest overall yields, with an average total yield of 38.3 tonnes/ha and a marketable yield of 29.2 tonnes/ha compared to the provincial average of 33.6 tonnes/ha (AF, 2019-2022). This is explained by generally hotter, drier conditions in 2021, and consistent with other work (Wagg et al., 2021) that has shown moisture stress to greatly reduce tuber yield. In 2022, the last year of this study, average overall total yields were 47.8 tonnes/ha and a marketable yield of 35.7 tonnes/ha. This was close to the provincial average for that year of 44.8 tonnes/ha (AF, 2019-2022).

Fig. 3.13 illustrates the trends in average marketable yield for each site in tonnes per hectare for each farm from 2019-2022, compared to the provincial averages for each year. Provincial yields are averaged among all the areas of all potato producer's fields, including both good-producing and poor-producing areas. Hand-harvesting plots, as was done to calculate total yield values for this research project, allows for the harvest of smaller potatoes that would be dropped by most potato equipment used on field scale by growers, so comparison of provincial average yields reported by growers to marketable yield values measured in this study is a more valid comparison.

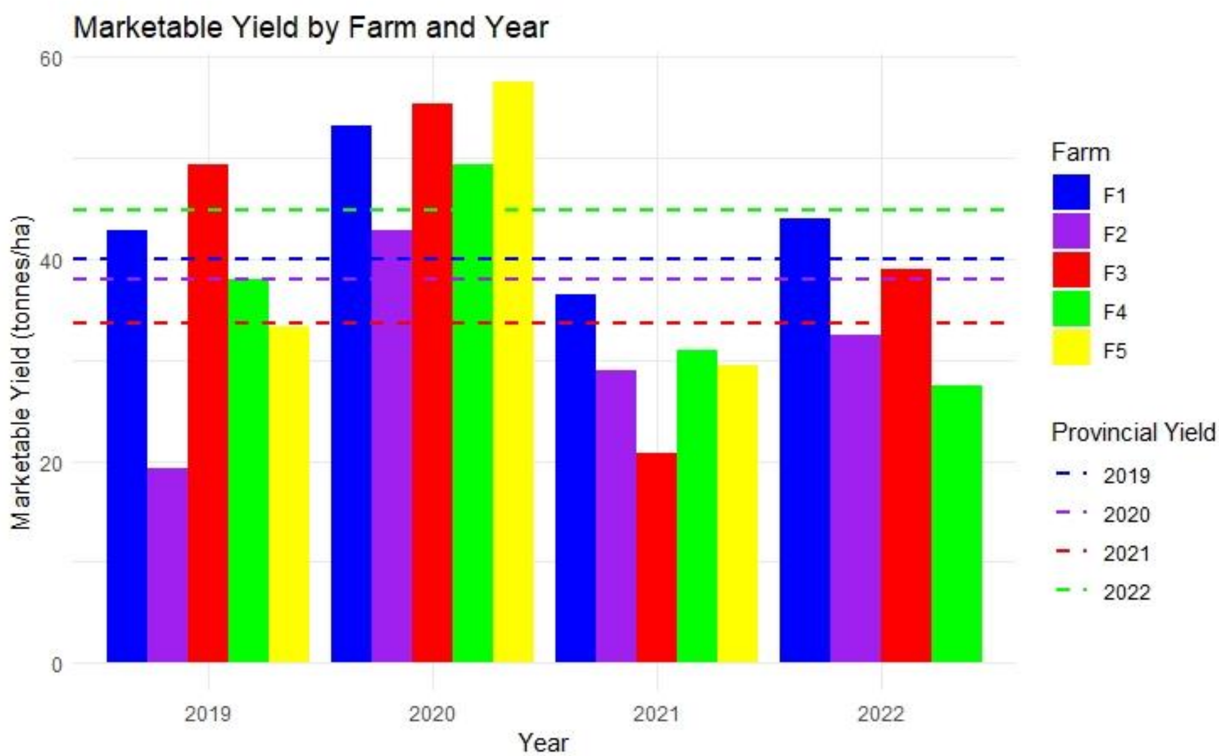


Fig. 3.13 Average marketable yield in tonnes per hectare for each site from 2019-2022, compared to the provincial average in tonnes per hectare for each of the four years.

The coefficient of variation (CV) expressed as a percentage was calculated to evaluate the degree of variability in the yield data. Higher CV values indicate greater variability. The CV values for both total and marketable yield (Table 3.6) vary across sites and years, where some sites experienced higher or lower yields. The F3 farm often showed lower variation in total yield, indicating a narrower range of yield fluctuations across most years. Conversely, the potato fields on the F4 farm demonstrated the highest CV values for total yield for all years. F2 and F4 farms have the highest average CV for marketable yields, while F3 farm has the lowest average CV over the 4 years for both total and marketable yield. The F1 farm exhibited the most consistent yields overall for marketable yield, with the lowest CV values in most years. This is likely a result of consistent management practices. The highest-yielding year, 2020, had the most consistent total and marketable yields with all sites having relatively low CV values.

Table 3.6 Coefficient of variation (%) for total yield and marketable yield by year and site from 2019-2022

	Year	**F1**	**F2**	**F3**	**F4**	**F5**
Coefficient of Variation for Total Yield	2019	13.5	36.0	9.5	25.8	30.7
	2020	18.2	11.4	10.2	11.3	15.7
	2021	11.1	21.1	16.8	20.8	12.8
	2022	11.9	13.7	11.7	29.0	X
Coefficient of Variation for Marketable Yield	2019	18.8	44.4	10.8	32.7	35.1
	2020	19.8	18.1	13.5	18.9	17.2
	2021	17.9	23.8	22.8	25.0	20.0
	2022	14.8	22.6	16.5	34.4	X

In PEI, Zebarth et al. (2021) also observed significant year-by-yield category interactions for many of the parameters, implying that yield-limiting factors will vary over the years. Precision irrigation methods can aim to improve the consistent yield of potatoes while accounting for factors such as soil moisture, topography, soil properties, temperature, and precipitation that influence yield. The use of best management practices customized for individual fields is key to optimizing yields (Ahmad, Sharma, 2023).

3.5.5 Statistical Modeling

This study sought to investigate the effect of several key factors, including available moisture, topography complexity, growing degree days (GDD), and soil complexity, on total yield and marketable potato yield. Consequently, the primary focus is on yield and understanding how it was influenced by the identified controlling factors. To accomplish this, eight linear mixed-effects models were used to analyze these relationships. The results, summarized in Table 3.7, present key metrics such as p-values, and slopes. In statistical modeling, the slope represents the effect of a predictor variable on the response variable (in this case, yield). A positive slope indicates that an increase in the predictor is associated with an increase in yield, while a negative slope signifies a decrease in yield with an increase in the predictor. P-values, on the other hand, indicate the significance of the relationship between a predictor and the response. A low p-value (typically less than 0.05) indicates a statistically significant relationship.

Table 3.7 Summary of statistical analysis results for different models investigating the relationship between various factors and potato yield under uniform irrigation. The table includes the p-values indicating significance levels for each factor, and the corresponding slopes.

			Tuber Initiation		**Tuber Bulking**	
		Depth	**0-35 cm**	**35-60 cm**	**0-35 cm**	**35-60 cm**
Total Yield	AM	p-value	0.53	0.09.	0.07.	0.04 *
		Slope	-0.03	0.10	0.11	-0.11
	Topography	p-value	0.002 **	0.001 **	0.002 **	0.0008 ***
		Slope	-3.26	-3.46	-3.36	-3.57
	GDD	p-value	0.17	0.13	0.12	0.13
		Slope	-0.04	-0.04	-0.04	-0.04
	Soil Complexity	p-value	0.35	0.44	0.25	0.27
		Slope	-3.98	-3.33	-4.91	-4.78
Marketable Yield	AM	p-value	1.00	0.16	0.04 *	0.01 *
		Slope	0.00	0.08	0.12	-0.14
	Topography	p-value	0.06.	0.05 *	0.05 *	0.03 *
		Slope	-2.00	-2.16	-2.10	-2.39
	GDD	p-value	0.44	0.42	0.38	0.41
		Slope	-0.02	-0.02	-0.02	-0.02
	Soil Complexity	p-value	0.62	0.73	0.49	0.49
		Slope	-2.14	-1.49	-3.01	-3.02

Note:

*: p-value < 0.1 (marginally significant)

**: p-value < 0.05 (significant)

***: p-value < 0.01 (highly significant)

Our analysis revealed varying levels of significance across the different models (Table 3.7). The available moisture during tuber bulking was found to have a significant effect on total yield as well as marketable yield, especially in the lower depths. This effect was positive in the 0-35cm depth and negative in the 35-60cm depth, suggesting that having excessive water in the lower part of the root zone has a negative effect on yield, but higher moisture in the upper depth increases yield. Topography, specifically 'not flat' topography, had a significant negative effect on yield during tuber initiation and tuber bulking for both total yield and marketable yield, with all but one p-value indicating significance. This indicates that flatter terrains might be more conducive to higher yields and underscores the need to consider topographic features when planning potato cultivation. The GDD, on the other hand, did not consistently show significance, even though in general the trend indicated a negative impact on yield, emphasizing that its influence may be dependent on other interacting factors. Soil complexity index did not have a significant impact on either total yield or marketable yield, though like GDD the trend was for it to have negative impact on yield.

Confidence intervals were calculated for each model to indicate the range of values within which the true parameter values are likely to fall based on the statistical analysis with 95% certainty (Table 3.8). For Tuber Initiation, the influence of AM at both depths may not be statistically significant as the confidence intervals span zero, suggesting that AM might not be a strong influencer of yield at this stage. In contrast, Topography exhibits a statistically significant negative impact on Tuber Initiation at both depths, as the confidence intervals do not contain zero. GDD values suggest no significance, as its confidence intervals range from negative values to positive values. Soil Complexity shows varying effects with a wide range in confidence intervals, also indicating no significance. For Tuber Bulking, confidence intervals suggest AM at 35-60 cm depth affects yield but may not consistently show significance at 0-35 cm. The negative values within the confidence intervals suggest a potential negative impact, particularly at the shallower depth. Topography, similar to Tuber Initiation, has a statistically significant negative influence on Tuber Bulking at both depths. The GDD confidence intervals as well as soil complexity do not indicate a potentially significant effect.

Table 3.8 Confidence Intervals for key variables of AM, Topography, GDD, and Soil Complexity at Two Soil Depths (0-35 cm and 35-60 cm) during Tuber Initiation and Tuber Bulking in Potato Crop Growth.

			Tuber Initiation		**Tuber Bulking**	
		Confidence Interval	**0-35 cm**	**35-60 cm**	**0-35 cm**	**35-60 cm**
Total Yield	AM	2.50%	-0.104	-0.014	-0.005	-0.219
		97.50%	0.056	0.211	0.220	-0.004
	Topography	2.50%	-5.312	-5.518	-5.403	-5.639
		97.50%	-1.202	-1.402	-1.309	-1.513
	GDD	2.50%	-0.084	-0.086	-0.087	-0.086
		97.50%	0.012	0.008	0.006	0.008
	Soil Complexity	2.50%	-12.404	-11.758	-13.167	-13.096
		97.50%	4.366	5.014	3.276	3.476
Marketable Yield	AM	2.50%	-0.080	-0.032	0.009	-0.252
		97.50%	0.083	0.198	0.238	-0.033
	Topography	2.50%	-4.097	-4.263	-4.185	-4.488
		97.50%	0.099	-0.058	-0.017	-0.296
	GDD	2.50%	-0.069	-0.069	-0.071	-0.070
		97.50%	0.029	0.028	0.025	0.027
	Soil Complexity	2.50%	-10.725	-10.143	-11.516	-11.516
		97.50%	6.357	7.074	5.417	5.407

The yield relation to topography index was consistently negative, similar to a study done in Atlantic Canada by Zare et al., (2019). They used a zonal analysis to determine that mean potato yield values were higher in areas where there were lower slope differences, and lower in areas with higher slope differences. They also found significant relationships between slope, elevation, and other soil parameters that influenced potato yields such as ground conductivity, horizontal coplanar geometry, and perpendicular coplanar geometry. A study done by Kravchenko and Bullock (2000) found that the cumulative effect of topography on soil factors explained up to 50% of yield variability on corn and Soybeans. Similarly, other studies such as Al-Gaadi et al. (2018), Muñoz, et al. (2014), and others have investigated the effects of topography on the yield of different crops. The topographic complexity indexes used in this study were developed specifically to examine the effects of topography and the impact it has on potato yield has not been assessed in other studies to date. Accounting for potato yield determining variables associated with topographic variability through precision water management approaches would therefore appear to be an effective approach to increase yield.

Soil complexity in this study showed no significant effect on yield, but there was a trend toward overall negative effects, with increasing complexity associated with reduced yield. The AM was also noted to have a significant negative effect on yield on two occasions. This observation is similar to that reported in a study done by Perron et al. (2018), who found that low-yielding areas for potatoes were often characterized by high (excessive) soil moisture content, and these areas were associated with higher clay content and poor drainage. Another study done by Zebarth et al. (2021) in PEI compared the coefficient in variation in soil parameters, as well as correlation coefficients for soil parameters to determine the effect of soil parameters on potato yields. They identified soil texture as being the most important factor limiting potato yield, most likely associated with its effect on water holding capacity both excess and insufficient. However, it was difficult to identify relationships between yield and soil properties due to low differences in mean values between high and low yields. Al-Hamed et al. (2017) also derived a soil and water quality index using soil texture and water quality. Though many studies have looked at the effect of soil parameters on potato yield and quality, the Shannon entropy method of calculating soil complexity used in our study has not previously been used to determine the effect of soil parameters on potato yield.

The differences observed in the direction and significance of the effects between the different models can be attributed to several factors. According to our model results, there were several significant correlations between yield and predictor variables. The most significant correlation was found between yield and topography, suggesting that variations in topography have the greatest impact on potato yield. Variable topography can result in variations in soil organic matter, fertility, and other soil factors that were not investigated in this study that would have contributed to the significance observed. When comparing the topography to the measured soil moisture data a general trend for higher variability in soil moisture was observed across fields with more variable topography, and more consistent moisture levels across flat fields. During the tuber bulking stage, available moisture in the upper root zone was also found to positively impact yield, while higher moisture in the lower root zone had a negative effect. This negative effect is likely due to waterlogged soils with poor aeration creating less than ideal conditions for tuber development and potentially higher disease occurrence (Li et al., 2006; Satchithanantham et al., 2012; Shock, 2007). There was also a general trend for lower CV values for both total and marketable yields in fields that had lower soil complexity and topographical complexity values.

The interactions and relationships among the predictor variables may influence how the effect of one predictor behaves when combined with others (Zare et al., 2019). The complex interaction of specific conditions of the study area, such as local climate, biological factors, soil conditions, topography or agronomic practices play a large role in variability in crops (Perron et al., 2018). From a statistical modeling perspective, these variations highlight the importance of recognizing that statistical models are simplifications of real-world processes. Different models make different assumptions about the relationships between variables, and these assumptions affect the interpretation of the results. Identifying yield limiting factors is a complex process, particularly considering that there is year by yield interactions that also limit yields, as well as factors that cannot readily be measured (Zebarth et al., 2021).

Efficiently using available irrigation water is the main goal of irrigation management. This helps regulate soil moisture levels for crops while encouraging their desired growth, reducing soil erosion, and protecting water quality (AF, 2011). For optimal potato growth, sufficient water supply during key stages of tuber initiation and early development is especially important (Akkamis, Caliskan, 2023), as also shown in this study. To ensure adequate soil moisture levels during peak water demand, farmers often implement regular, light irrigation when natural rainfall is insufficient, promoting vigorous potato growth. This is especially important during the flowering and tuber bulking growth stages when water demand is at its peak. Modern sprinkler irrigation systems are a reliable solution for meeting the crop's water requirements during this critical period of growth (AF, 2011). The results of this thesis work indicate that soil available moisture, soil complexity, and topography variations are potential drivers of potato yield and are worthy of consideration in irrigation development and precision management.

3.6 CONCLUSIONS

This research examined how the variability in topography, soil properties, soil hydrological conditions, and weather affected the yield of potatoes in southern Alberta. It was concluded that the factor that had the most significant influence on yield was topographic complexity, specifically land that was classified as 'not flat' or had more variable topography. This class of topography was shown to have a significant negative impact on yield during both tuber initiation and tuber bulking. Soil hydrological conditions were also seen to have a significant effect on tuber yield, particularly during tuber bulking. The impact of GDD as part of "weather" did not have a significant impact on yield, though a negative trend was observed in all models. However, it is important to note the relatively close proximity of the five different study sites. Similarly, soil complexity did not show a significant relationship with yield, though it too exhibited a trend of negative effect on tuber yield.

There are many interactions among the different predictor variables in the study areas. The statistical models used were simplifications of the complexity encountered under actual field conditions that contribute to the variation in the results. The complex interactions of the different factors in potato fields create unique growing conditions that will vary from field to field, and year to year. In this study using potato fields at five sites in southern AB, the topographic complexity, soil available moisture and complexity, were identified as drivers of potato yield, suggesting the importance of their consideration in irrigation development and precision management. The observed variations in soil and topographical complexities show the importance of site-specific and temporally adaptive management approaches. This study highlights the importance of precision irrigation to address soil moisture variations and improve potato crop yield in southern Alberta. The complex nature of the different factors influencing potato yield emphasize the need for a detailed understanding of variables in optimizing potato production. It is anticipated that understanding and accounting for these variations in soil and hydrological conditions will lead to more effective precision irrigation strategies and ultimately result in improved potato yield and quality (Danielescu et al., 2022). The expected benefits include improved water efficiency, minimized environmental impacts, and sustained high-quality potato yields, making precision irrigation a vital tool for sustainable agriculture in the region (Danielescu et al., 2022).

4 Use of Predictive Irrigation Technologies and Variable Rate Irrigation for Precision Irrigation on Potatoes in Southern Alberta

4.1 PREFACE

Improving irrigation management is becoming increasingly important in Southern Alberta resulting in more producers looking for ways to improve water use efficiency and yields. This study examines integrating the Alberta Irrigation Management Model (AIMM) and Variable Rate Irrigation (VRI) technologies into current irrigation practices. This study specifically aims to analyze the effectiveness of predictive methods for water management for potato production in the region.

4.2 ABSTRACT

Soil moisture, as shown in Chapter 3 of this thesis, is a key driver of potato yield. Precision irrigation accounts for the variability in soil properties, topography factors, and subsoil constraints, to improve water application, available water and crop productivity while conserving water resources and reducing water costs. Predictive irrigation scheduling models that take into consideration variable soil conditions along with weather and drive variable rate water application can help optimize water use efficiencies. The primary objective of this two-year observational study was to investigate the effectiveness of predictive irrigation scheduling at predicting soil moisture in a potato field. This two-year study, conducted at the Integrated Agriculture Technology Center (IATC) farm near Lethbridge, Alberta from 2021-2022, monitored soil moisture along a transect with variable topography under a low-pressure center pivot equipped with variable rate irrigation (VRI). Soil moisture was monitored using a neutron probe, and the Alberta Irrigation Management Model (AIMM) was employed to guide irrigation practices with and without the input of neutron probe measurements. Weather parameters, including precipitation, accumulated evapotranspiration, and growing degree days, differed between the two growing seasons. The VRI application aimed to tailor irrigation practices to crop requirements using real-time data to maintain a consistent soil moisture across the field. The relationship between yield and soil moisture was compared between monitoring points, and no significant relationship between yield and moisture was found, indicating success in the ability of predictive scheduling and VRI in reducing this source of yield variability. The study also assessed the accuracy of AIMM by comparing the model run without soil moisture corrections to the model run with soil moisture corrections. Model reliability was found to be higher in 2022 than 2021. Use of regular soil moisture monitoring is recommended to producers to use the AIMM software most effectively. The proper use of predictive irrigation scheduling models can assist producers in making informed irrigation decisions.

4.3 INTRODUCTION

Canada is considered a water-rich nation, accounting for almost one-fifth of the world's water supply. However, some regions of Canada, particularly Southern Alberta, experience water scarcity challenges (Shapiro, & Summers, 2015) and innovative water management strategies are needed. Agriculture is considered the largest consumer of water in Canada (Ghaderi et al., 2011), and there is increasing pressure on irrigated crop production to reform water management by improving the efficiency of water use (Klein et al., 2012). In regions like Southern Alberta, where water availability is limited, the need to improve water use efficiency using precision irrigation technologies has long been recognized (Nicol et al., 2008).

There are various precision irrigation technologies available that offer the means to account for in-field variability, monitor water use efficiency, and assess the impact of irrigation management on potato yield in Southern Alberta (Neupane & Guo, 2019). These technologies include the use of soil moisture sensors, predictive irrigation systems, yield mapping, and Graphical Information Systems (GIS) for precise water application (Ahmed, Sharma, 2023). In southern Alberta, the majority of the uptake of precision irrigation technologies is found on specialty crops (Nicol, Nicol, 2021). Using precision irrigation technologies to account for spatial and temporal variability in fields can be a very powerful tool for producers to optimize water use in a water-limited environment (Evans, King, 2010), improve crop productivity, and ultimately increase profitability (Yari et. al. 2017). For precision irrigation to be effective, the different factors that result in variability within a field must be considered. These factors may include, but are not limited to, soil properties (e.g., texture, fertility, electrical conductivity, organic matter), topography factors (e.g., slope, gradient, elevation), and subsoil constraints (e.g., density, salinity) (Li et al. 2007; de Lara et. al. 2018).

Implementing predictive technologies to meet the crop's specific water requirements using real-time information on soil conditions and crop growth in various areas of potato fields can allow producers to make data-driven, informed decisions based on the specific field conditions and needs of potato crops (Ahmed, Sharma, 2023). The use of predictive irrigation technologies provides the opportunity for producers to improve their irrigation management and optimize yield and quality. The uptake of these technologies has not been widespread in Southern Alberta (Nicol et al., 2010), and additional research is needed to assess their feasibility, effectiveness, and potential impact on improving water use efficiency, crop productivity, and overall sustainability in the region.

The primary objective of this two-year observational study is to investigate the use of predictive irrigation technologies in potato production. Specifically, effectiveness of the Alberta Irrigation Management Model (AIMM) for predicting irrigations and managing soil moisture is assessed. By analyzing the performance of this precision method, we seek to identify the effectiveness of incorporating it as a precision water management strategy for potato cultivation in Southern Alberta.

We hypothesize that predictive irrigation scheduling methods that account for the inherent variations in soil hydraulic characteristics and crop water requirements will effectively account for changes in soil moisture and result in increased water use efficiency and potato yield. We anticipate this technology will result in more targeted and optimized water applications throughout the growing season. In this study, we aim to answer the following question: How effective are predictive irrigation technologies at estimating soil moisture in a variable field? The findings of this study will provide additional information to producers considering the use of precision irrigation technologies to optimize potato production and water use efficiencies.

4.4 MATERIALS AND METHODS

4.4.1 Field Characterization

4.4.1.1 Site Selection

A 2-year study (2021-2022) was conducted at the Integrated Agriculture Technology Center (IATC) farm in Lethbridge Alberta, managed by Lethbridge College. The field used in this study was a 27-ha parcel irrigated by a 5-span low-pressure center pivot equipped with Variable Rate Irrigation (VRI). The irrigation circle is divided into quarters, with each quarter farmed as a separate field. Due to rotation requirements, the same field could not be monitored in both years, so there were different levels of topographic and soil variation creating two unique field years. A transect was chosen each year to represent the variations of topography within the field, with 5 locations along the transect including 2 ridges, 2 mid slopes, and one valley site (Fig. 4.1). Potatoes were seeded and managed according to agronomist recommendations throughout the year, and the variety Russet Burbank, was used in both years. Factors such as land preparation, tillage, nutrient, and crop protection management remained consistent across both years and were not directly considered in this analysis.

4.4.1.2 Soil Texture

The texture at each sample point varied from sample point to sample point and is shown in Table 4.1. Soil texture was determined using the hydrometer method (Gee and Bauder, 1986). Soil texture across transects each year ranged between Loam, Clay Loam and Sandy Clay Loam textural classes at each of the sample sites for the field used each year, with the points in valleys generally showing a higher proportion of clay- sized fraction. At most transect points, the clay content increased as the depth in the profile increased.

Table 4.1 Soil textural classes in the soil profile of each sampling point along the 2021 and 2022 transects.

<table>
<tr><td></td><td colspan="5">2021</td><td colspan="5">2022</td></tr>
<tr><td>Depth (cm)</td><td>P1</td><td>P2</td><td>P3</td><td>P4</td><td>P5</td><td>P1</td><td>P2</td><td>P3</td><td>P4</td><td>P5</td></tr>
<tr><td>0-15</td><td>SCL</td><td rowspan="3">SCL</td><td rowspan="8">CL</td><td>CL</td><td rowspan="6">L</td><td rowspan="2">L</td><td rowspan="7">SCL</td><td>SL</td><td>SL</td><td>SL</td></tr>
<tr><td>15-30</td><td rowspan="3">L</td><td rowspan="2">L</td><td>SCL</td><td>SCL</td><td>SCL</td></tr>
<tr><td>30-45</td><td rowspan="5">SCL</td><td rowspan="6">CL</td><td>CL</td><td rowspan="6">CL</td></tr>
<tr><td>45-60</td><td>CL</td><td>SCL</td><td rowspan="3">SCL</td></tr>
<tr><td>60-75</td><td rowspan="3">SCL</td><td rowspan="2">SCL</td><td rowspan="2">L</td></tr>
<tr><td>75-90</td></tr>
<tr><td>90-105</td><td rowspan="2">CL</td><td rowspan="2">CL</td><td rowspan="2">SCL</td><td rowspan="2">CL</td></tr>
<tr><td>105-120</td><td>CL</td><td>CL</td><td>CL</td></tr>
</table>

4.4.1.3 Elevation

A transect was chosen each year to represent the spatial variation across the field, with 2 points representing ridges, two points representing mid slopes, and one point representing a depressional valley. A topographical position index map (Weiss, 2001) was created in 2022 of the study fields from elevation data obtained with an eBee Plus UAV (Fig. 4.1). Points along the transects for each of the two years are indicated in relation to the topography they represent. The different positions along the transect allow the moisture levels to be independently considered and accounted for in the application of precision irrigation and VRI.

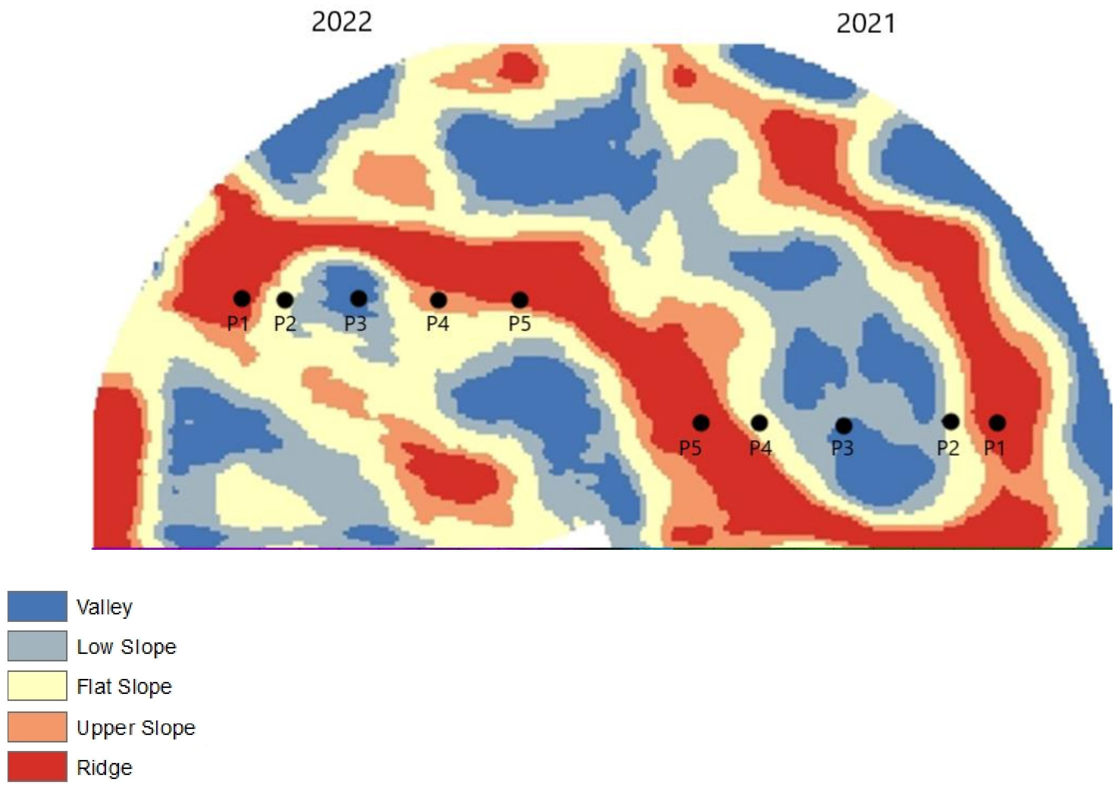


Fig. 4.1 Topographical position index map created showing sampling points in 2021 and 2022.

Topography varied between the two fields used in this study, and the differences in elevation were documented for each of the points in 2021 and 2022 (Table 4.2). The elevation difference among transect points was more pronounced in 2021.

Table 4.2 Elevation in meters for each of the transect points in 2021 and 2022.

Point	2021	2022
P1	903.5	903.1
P2	903.1	902.9
P3	900.4	902.1
P4	901.6	903.4
P5	903.4	903.9

4.4.1.4 Soil Moisture

Neutron probe access tubes were installed in parallel along the transect each year beside each transect point before tuber initiation, with a 10-row separation at each sample site. In the 2021, the access tubes were installed in the potato hill to a depth of 1.5 meters using a hand auger, and in 2022, they were installed to a depth of 1.2 meters using a hydraulic coring machine. Soil samples were collected at each point in 15 cm depth increments and analyzed for soil moisture, bulk density, and soil texture (Table 4.1). Neutron probe measurements were taken for VWC each week at 15 cm intervals at each access tube across the transect. Soil moisture content was assessed on a weekly basis, and changes to the VRI prescription were made if needed.

4.4.2 Irrigation Management

The Alberta Irrigation Management Model (AIMM) was used to model and predict the soil moisture throughout the season. To initiate this model, potatoes were selected as the crop, seeding dates were entered and irrigation system information was entered. Sample sites were created for each neutron probe access tube to provide the most detailed overview of soil moisture conditions throughout the field. For each sample site, textures were inputted in 15cm depth increments to allow the software to generate available moisture, and an allowable depletion point of 35% was set with a 0.6m rooting depth. The model was initiated using the first neutron probe readings on the day of installation, and the Lethbridge weather station data was uploaded. Throughout the season weather data was refreshed and irrigation amounts were added. Where the VRI prescription resulted in a differing amount of irrigation applied, adjustments were made manually for the affected sample site.

Two simulations of AIMM were run, the first model without any corrections to the predicted soil moisture after the initial VWC measurement was added, and the second model where soil moisture level in the model was corrected to match the weekly neutron probe moisture readings. This information was used to make real-time adjustments to irrigation prescriptions, which had a goal of creating uniform soil moisture levels throughout the entire field, and to compare model performance to field conditions. By doing so, we aimed to optimize water usage and enhance the overall efficiency of irrigation practices and compare the effectiveness of the model with and without field monitoring.

4.4.3 Variable Rate Irrigation

This pivot was retrofitted with a VRI zone control package from Valmont (Valmont Industries Inc, Omaha, Nebraska, USA), with 12 zones consisting of 10-12 sprinklers each. Zones are controlled using a single electric solenoid valve that turns the zone on or off to maintain the application depth defined in the prescription. VRI was used to precisely tailor irrigation practices to the specific requirements of the potatoes under study. By utilizing real-time data and soil moisture measurements, we aimed to deliver irrigation precisely to meet the crops' immediate needs by creating variable rate prescriptions based on weekly moisture data (Fig. 4.2). These prescriptions were not changed after the initial creation, as moisture variability throughout the season did not warrant it. In 2021 excessive moisture was consistently seen in the depression along the transect, which in past years of production has resulted in loss of yield due to excessive water. This necessitated a reduced application rate for that area to create a more uniform moisture level across the field and reduce the risk of excess water causing a reduction in yield. A 15% reduction was chosen, which is equivalent to a reduction of 2.67 mm per irrigation event when the base application was 17.8 mm. In 2022 a blanket rate was chosen along the full transect, as the variation in soil moisture along the transect did not necessitate a difference in application. The 85% setting was chosen as a different research project located next to the transect required over-applications of water which served as the 100% base setting. In other words, the 85% setting was equivalent to the optimal water application required by the potato crop.

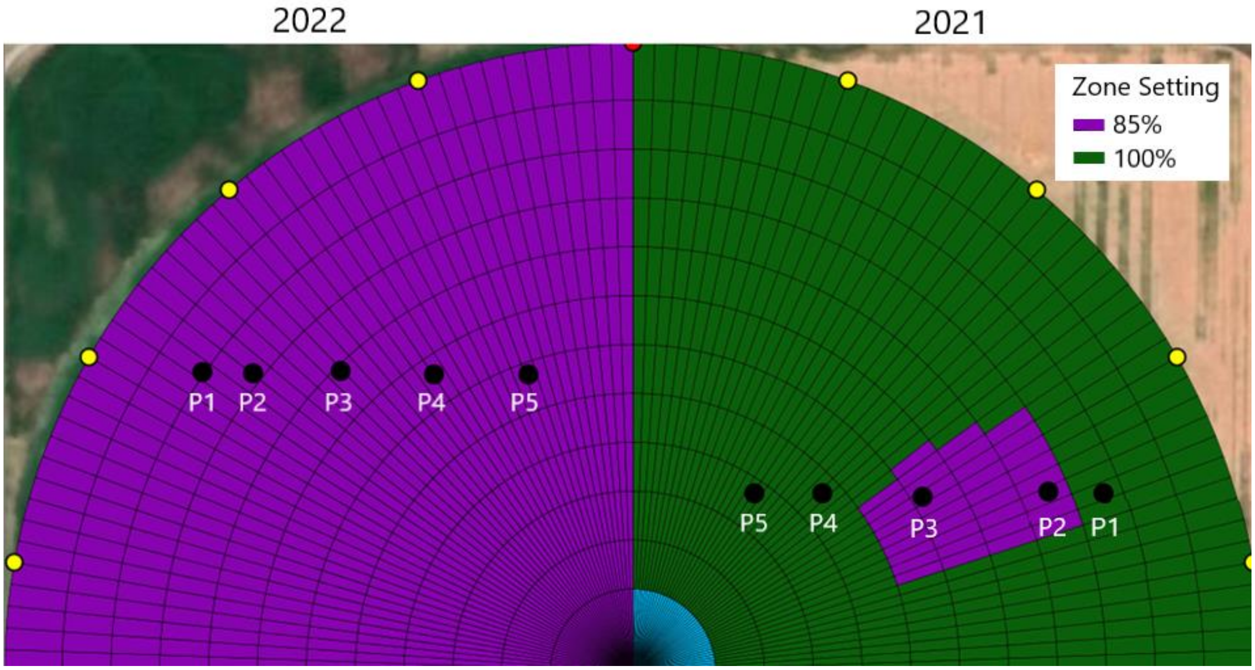


Fig. 4.2 VRI water application prescription showing the distribution of water applied in 2021 and 2022.

Can tests were also performed under this pivot during the first season to verify the accuracy of the VRI system. This involved setting up two collection cans under each sprinkler and setting a prescription with incremental increases of 10% along each irrigation zone. The collected moisture was then measured and compared to set values to determine accuracy.

4.4.4 Data Analysis

4.4.4.1 Soil Moisture

Soil texture data was utilized from each site to determine field capacity (FC) and wilting point (WP) for each of the samples collected. The average % sand, silt, and clay of each soil layer were entered into the pedotransfer module of SPAW Hydrology 6.0 software (USDA, 2023) to get a base value for FC and WP. This software estimates soil water tension based on texture and organic matter, with adjustments for density, gravel, and salinity using a set of empirical equations (Rawls et al., 1982; 1992; 1998; Saxton et al., 1986). Due to the high spatial and temporal variability in the hydraulic properties of soils, the lack of representation for soil structure, and other limiting factors, it was necessary to adjust these estimated values based on field soil moisture observations at each monitoring site. These estimated values were adjusted using VWC data collected from neutron probe measurements and GWC values, then adjusted as needed based on measured values, observations, and trends.

Once the levels for FC and WP were established, VWC data was converted to available moisture (AM) using equation 1.

$$AM = \frac{VWC - WP}{FC - WP} * 100 \qquad [1]$$

Where AM is available moisture expressed as a percentage between 0 and 100, FC is field capacity expressed as a decimal fraction and WP is wilting point expressed as a decimal fraction.

Percentage available moisture is a function of soil texture, and water holding capacity. Where VWC measures the volume of liquid per volume of soil, available moisture will indicate that level as a percentage within the range between permanent wilting point and field capacity. The ideal AM range for potato production within the rooting zone is 65-100% available moisture (AF, 2016). This will ensure the crop has adequate moisture to meet crop needs throughout the growing season.

4.4.4.2 Water Use Efficiency

Water use efficiency was calculated by comparing the average yields collected from each point along the transect to the total water application over the growing period. Adjustments to total water consumption were made to consider the points where the application rate was adjusted using the VRI prescription. This was done using equation 2:

$$WUE = \frac{Yield}{Total\ water\ input} \qquad [2]$$

Where WUE is water use efficiency in tonnes/ha/mm, yield is total tubers collected in tonnes/ha and total water input is the total mm of water added to that location including rainfall and irrigation.

4.4.4.3 Yield and Quality

At the end of each growing season, three subplots were harvested at each monitoring point. Harvest was done prior to the full field harvest and occurred between the last week of August and the first two weeks of September each year of the study. Three rows were selected at each point to harvest for total yield. From each of these rows, a 6m section was marked and tubers were dug with a one-row potato digger, and samples were collected in mesh bags, and labeled individually as replicates 1-3.

For each replicate of tubers harvested, the number and weight of tubers in these samples were determined by weight class. Weight classes were 0-113g, 113-170g, 170-284g, 284-396g, and 396 g+. Deformed tubers were weighed separately, as were tubers damaged during harvest. Total yields were calculated by adding all the weight classes together, and marketable yield was calculated by adding tubers greater than 170g (6oz). Yield was first calculated as kg/m^2, based on a plot size of 36" by 236" (6m). This plot size represented the 6m sections that were hand-harvested, and the 36" row spacing between potato hills. These values were then converted to tonnes/ha.

One subsample of 25 non-damaged tubers was taken from each site sample after weighing to determine the frequency of external and internal defects such as hollow heart, brown center, vascular discolor, flesh color, scab, and scurf. Tubers selected were 113g or greater in weight and were cut in half along their longest axis and arranged with half in a 5x5 grid with the flesh facing upward, and the other half in a 5x5 grid with the flesh facing downwards. Another subsample of 25 tubers was brought to a commercial lab (Independent Crop Inputs Inc.) immediately following harvest for analysis of specific gravity, sucrose, and glucose.

4.4.5 Statistical Analysis

To investigate the relationship between corrected and non-corrected soil moisture values obtained from AIMM, the Nash-Sutcliffe efficiency coefficient (Nash & Sutcliffe, 1970) was calculated for each entry of the timeseries. The root mean square error (RMSE), quantifying the average prediction error was also calculated to analyze model performance. The effect of precision irrigation on yield was assessed using a linear regression in R Statistical Software (R Project, 2023). The statistical analysis aimed to investigate the impact of soil moisture levels on crop yield in a transect over two consecutive years for averages of percentage available soil moisture at 50% and 100% of the root zone. The linear regression models were implemented using the lm () function in R Statistical Software (R Project, 2023).

4.5 RESULTS AND DISCUSSION

4.5.1 Accuracy of the VRI system

Two different tests were conducted on each zone of the pivot used in this study to evaluate the accuracy of the VRI system application using two different prescriptions. The results of these two tests can be seen in Fig. 4.3.

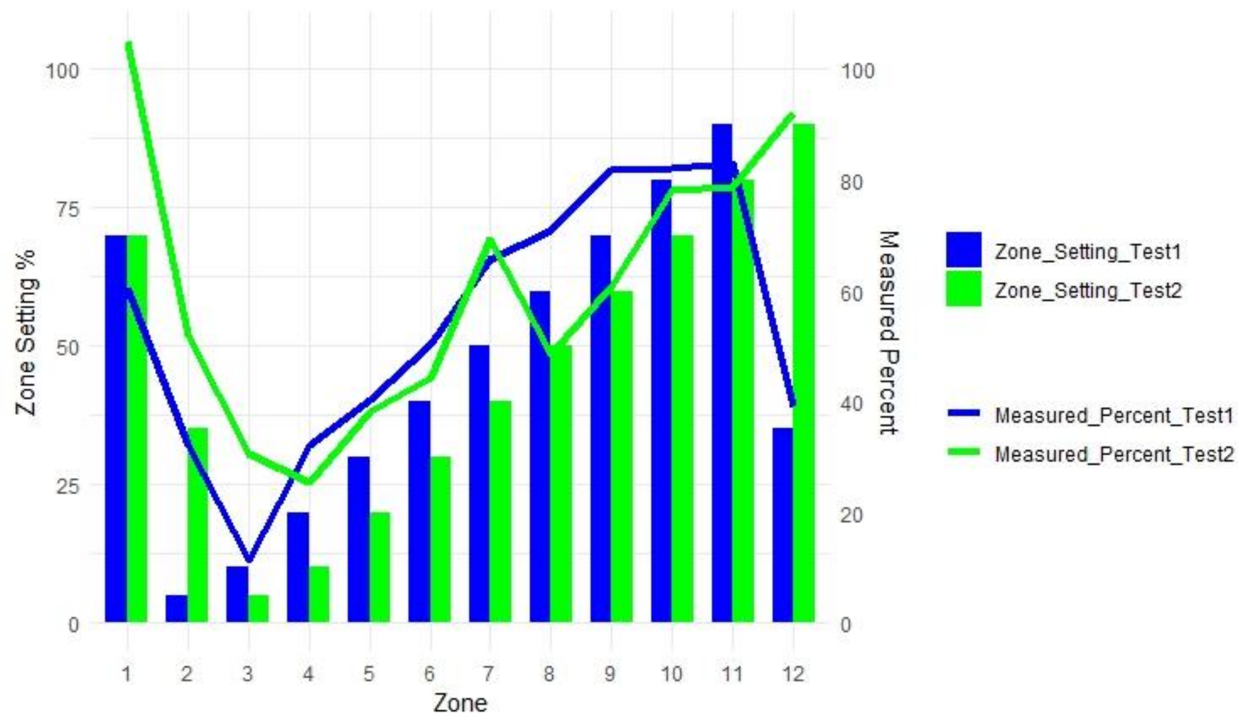


Fig. 4.3 Results of two can tests conducted in 2021 to assess the accuracy of the VRI system on the pivot used in this study. Prescription settings are indicated by bars, where the measured application is indicated by the lines for the two different tests.

It was found that generally the lower the application percentage the zone was set at, the higher the discrepancy in the actual application rate. However, the zone closer to the pivot center (zone 1) had higher discrepancies in application despite having a higher application rate, whereas the zones furthest from the pivot center were generally more consistent, even if set lower. This is likely due to the throw radius of the sprinklers in the smaller zones causing an overlap, the speed of the pivot in that zone, as well as the drainage from the sprinklers as the valves turn on and off. The zones closer to the pivot tower are much narrower resulting in less area for these inefficiencies to be spread over.

4.5.2 Soil Moisture

Volumetric Water Content

VWC data was averaged between the two access tubes at each sampling site throughout the growing season for each year (Fig. 4.4). Moisture was variable throughout both seasons, with much of the variation seen in the top 30 cm of each transect point due to irrigation events having a limited infiltration depth, potato root water uptake being concentrated in the top 30 cm of the soil, and evaporation taking place along the sides of the potato hills. The effective root zone for potatoes typically extends to 0.6 m in depth, so the moisture in the depths below would be mostly unused by the crop. This trend was observed consistently throughout the season, with consistently less variation in VWC values with depth in 2022 compared to 2021. This may be explained by the field used in 2022 having less variability in topography. The VWC values for the five points for 2021 and 2022 seasons are shown in Fig. 4.4. In 2021 two points (P2 and P3) received less water, and this helps explain the lower average VWC levels through the field. In 2022 all five points were subject to the same irrigation application rates.

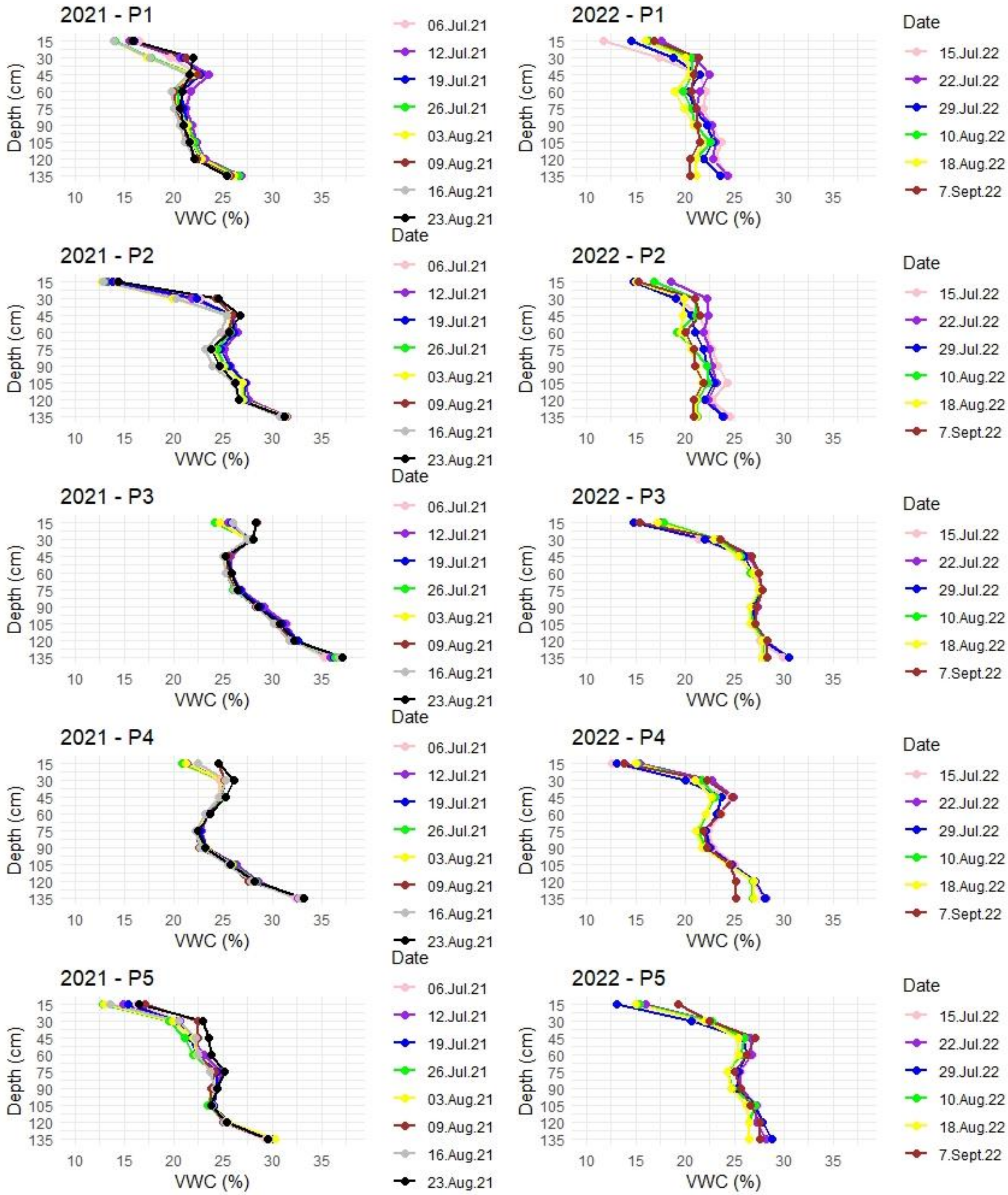


Fig. 4.4 Average VWC profile on eight (2021) and six (2022) dates for each point along the transect during the growing season.

The increasing clay content at depth contributes to the greater VWC, especially in the 2021 field. Moisture values throughout the season below one meter remained quite high, often at or above field capacity, particularly in the low point, representing unused stored soil moisture. In 2022, the field area used had texture that was more consistent throughout the profile, ranging from loam in the upper profile to sandy clay loam and clay loam in the lower profile (Table 4.1). The VWC values were more consistent with depth moving below the 0-60cm potato root water uptake zone and varied more among measurement times in 2022 than the year prior. The variation in moisture below the root zone is likely due to other hydrological processes happening in the soil such as groundwater interactions and percolation.

Potatoes are grown on widely spaced rows which considerably exceeds the sphere of the neutron probe, especially in wet soils. This factor combined with other factors that can contribute to error such as calibration, installation, and settings, can lead to considerable inaccuracies in determination of soil moisture (Gaze et al., 2002). The VWC values determined in the upper half of the root zone using the neutron probe approach were consistently lower than expected compared to field observations, gravimetric moisture determined on samples, and expected based on soil textures. This was observed mostly in the 0-15cm depth, and to some degree in the 15-30 cm depth as well. Gaze et al. (2002) conducted a study analysing the effectiveness of measuring soil moisture content using a neutron probe in potatoes. They found considerable inconsistencies in neutron probe measurements, particularly in the potato hill. Another study done by Foroud et al. (1993) found inaccuracies in the potato hill as well, with moisture readings often being influenced by the high moisture content of the tubers within the hill as well. They did not observe these inaccuracies in the lower part of the profile. Due to the inaccuracies in this study, when VWC values were converted to percentage available moisture, the 0-15cm percent available water values were discarded, and the 15-30 cm reading was used to represent the entire hill.

Available Moisture

Soil AM levels varied over each season along the transect, due to water lost from ET and water added through rainfall and irrigation. AM levels were averaged for three groups, in hill (15-30cm), below the hill (30-60cm) and below the root zone (60-120cm) for each point along the transect. Most measured values remained within our management allowable depletion level as seen in Fig. 4.5, with less variation as we moved down the soil profile. A higher range of variation was seen in hill in both 2021 and 2022 compared to below the hill, with greater fluctuations in 2021 with several values exceeding field capacity. In 2022 the moisture levels tended to stay within the optimum or ideal management zone. The higher variation in the hill was likely due to the lower bulk density of the soil, and the water uptake by the plant. Other studies have modelled similar variation within the root zone, including a study done by Starr et al. (2008), that found that the greatest uptake of water was found in the potato hill, and significantly less below the hill. Below the hill in the 30-60 cm depth, there was a reduction in variability compared to the in-hill values for both the 2021 and 2022 year, with an increase in the variability towards the end of the season in both years. In 2021, values below the hill were sometimes above field capacity, where in 2022 the moisture levels slowly decreased throughout the season indicating more drainage than the previous year. When looking at the moisture levels below the root zone, the variation is less than the variation within the root zone, and a slow decline was observed in both years as water drained from the profile, though values generally remained either at or above field capacity.

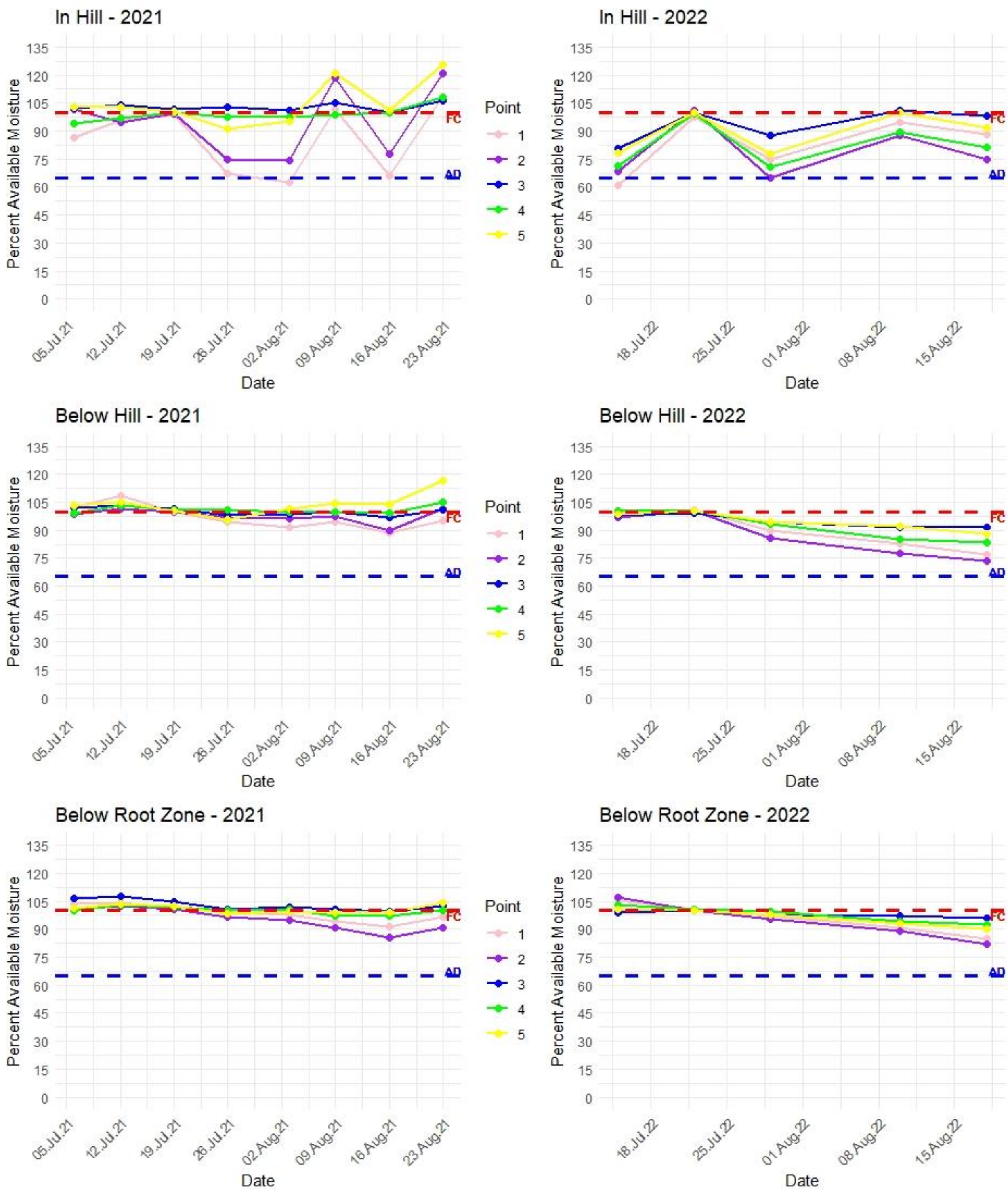


Fig. 4.5 Variations in percentage of available soil moisture levels at different depths (In Hill – 0-30 cm, Below Hill – 30-60 cm, Below Root Zone – 60-120 cm) during the years 2021 and 2022. The horizontal dashed lines represent field capacity (FC) at 100% AM (dashed red line) and the Allowable Depletion (AD) at 65% (dashed blue line). The colored lines represent the moisture measurement points along the transect over each growing season.

The spatial and temporal variations in soil moisture observed in this study are similar to that reported in other research. Star (2005) conducted a study observing soil water patterns along field transects, observing variations along different topographies and soil textures. They found that soil texture had the greatest influence on soil moisture, with coarser soils generally drier. This aligns with our study as we observed lower moisture levels at the points that had higher sand content, and higher moisture levels where clay was predominant. We also saw this trend between years as lower moisture levels were observed in 2022 when textures were generally sandier, though other factors such as ET, rainfall, GDD and irrigation would have also inherently played a role. Star (2005) also noted the multi - year trends in soil moisture that persist despite different crops being grown. The field our study was located on has a history of poor drainage in the depressions, and in some years these areas have standing water during parts of the season. A study done by Satchithanantham et al. (2014) in Manitoba monitored the soil moisture levels throughout the root zone of potatoes as well as moisture levels below the root zone. They found increasing moisture levels below the root zone with successive irrigations. With shallow groundwater levels, capillary rise from the groundwater reservoir contributed to the crop's water needs. The variations observed in moisture levels below root zone in the current study were likely also affected to some degree in the same way. Satchithanantham et al. (2014) also observed a higher variation in soil water content in surface layers, with less fluctuation further down the rooting zone, similar to our observations. In the current study, soil moisture levels mostly remained within our management allowable depletion, indicating an effective water management strategy.

4.5.3 Weather

Weather data was collected using the Lethbridge Demo Farm IMCIN weather station for the growing season from May through September of 2021 and 2022. Seasonal temperature values including average minimum temperature, average maximum temperature, and average temperatures in 2021 and

2022 are shown in Fig. 4.6. In 2021 there was a “heat dome” effect, which resulted in higher-than-normal temperatures throughout the growing season. While the seasonal averages for the two years were not very different, the distribution of when the high temperatures were observed throughout the season was different in the two years. In 2021, the higher temperatures occurred much earlier in the season, whereas in 2022 there was a more gradual increase in temperature moving into summer.

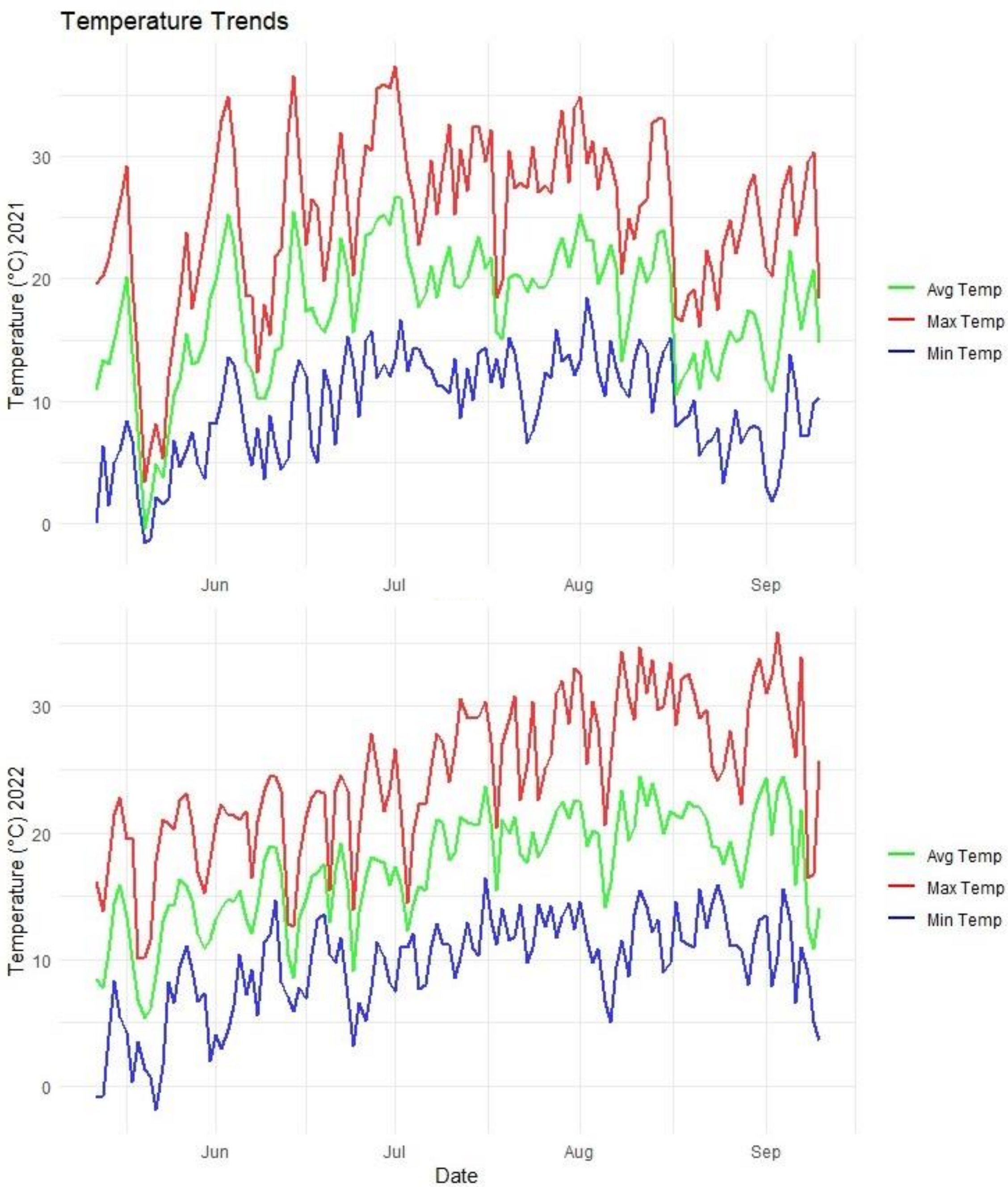


Fig. 4.6 Minimum, maximum, and average temperatures in °C throughout the growing season for 2021 and 2022.

The differences in the temperature values were also manifested in the days over 30°C and days over 35°C as shown in Table 4.3. The 2021 growing season had 4 more days over 35°C than 2022, and 3 more days over 30°C. Seasonal averages for maximum and average temperatures were also higher in 2021 than 2022.

Table 4.3 Seasonal temperature values for 2021 and 2022. Temperature values are shown as the seasonal average.

	Days over 30°C	**Days over 35°C**	**Max temp °C**	**Avg. Temp °C**	**Min Temp °C**
2021	30	5	24.9	17.4	9.4
2022	27	1	24.5	17.1	9.4

The temperature differences between the two years also impacted crop water used through ET, and what was supplied in irrigation (Fig 4.7). Irrigation amounts shown are for the highest zone setting for each prescribed year. Accumulated ET was observed to be 487 mm in 2021 and 468 mm in 2022. The distribution of water input (rainfall + irrigation) was also quite different between the two years. In 2021, rainfall contributed 125 mm, while irrigation accounted for 294 mm, resulting in a total water input of 419 mm. The 2022 season experienced higher rainfall amounts totalling 241 mm, and lower irrigation amounts of 227 mm, leading to a higher overall water input of 467 mm.

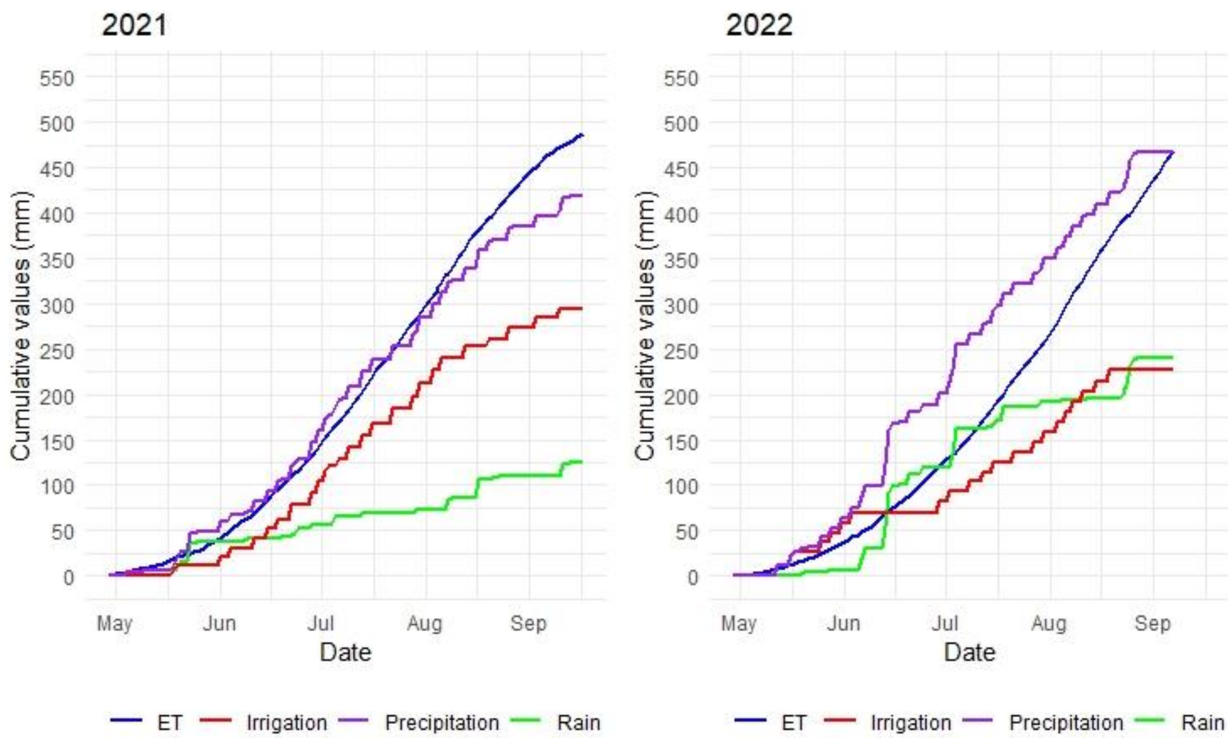


Fig. 4.7 Accumulated ET, Irrigation, Rain, and Total Precipitation Water Input (rain + irrigation=) in mm for the 2021 and 2022 growing seasons. Irrigation amounts shown indicate the highest zone setting for the appropriate year.

The GDD values were also summed for each growing season and compared between the two years. A higher number of growing degree days were also observed in 2021 than 2022 due to the heat dome event (Fig. 4.8). Cumulative GDD values totalled 1298 in 2021 and 1212 in 2022.

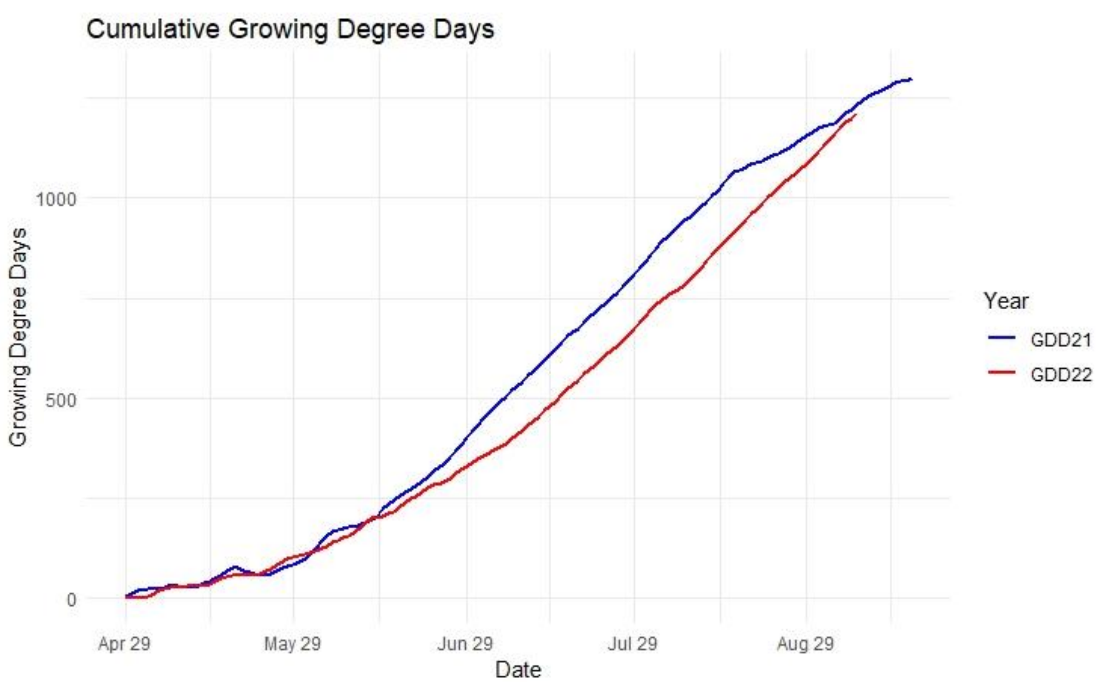


Fig. 4.8 Cumulative growing degree days for 2021 and 2022 throughout the growing season.

Weather conditions play a key role in potato production in southern Alberta. Potatoes are a temperature sensitive crop, particularly in terms of extreme temperatures during key times in their development (Adekanmbi et al., 2023). Potatoes require a certain amount of accumulated heat or GDD to complete their life cycles (Rodríguez et al., 2016), but excessive heat can be a negative determining factor in their growth and development (Cao & Tibbitts, 1994). The heat dome event in 2021 resulted in elevated temperatures throughout the growing season, higher growing degree days, and higher evapotranspiration. Precipitation is also a key factor in tuber growth and development, and the drier, hotter conditions experienced in 2021 resulted in the need for more irrigation, while the cooler temperatures and higher rainfall experienced in 2022 resulted in less irrigation. Insufficient water application can result in water stress, stunted growth, and reduced tuber formation (Wagg et al., 2021), while excessive application can lead to water accumulation and waterlogged conditions, increasing the risk of root diseases and reducing potato yield (Li et al., 2006; Satchithanantham et al., 2012; Shock, 2007). The combination of these weather-related factors directly impacts the success and productivity of potato crops.

4.5.4 Yield and Water Productivity

Potato yield was found to be variable across the transect, and between years. There are many different factors that can influence the variability of potato yield across a field in any given year, particularly soil moisture and physical, chemical, and biological soil properties (Po et al., 2010). With a change in field location each year, a difference in the degree of variability in yield was also expected. External factors, especially weather patterns can affect yield levels from year to year as well. Variability between points and years is shown in Fig. 4.9.

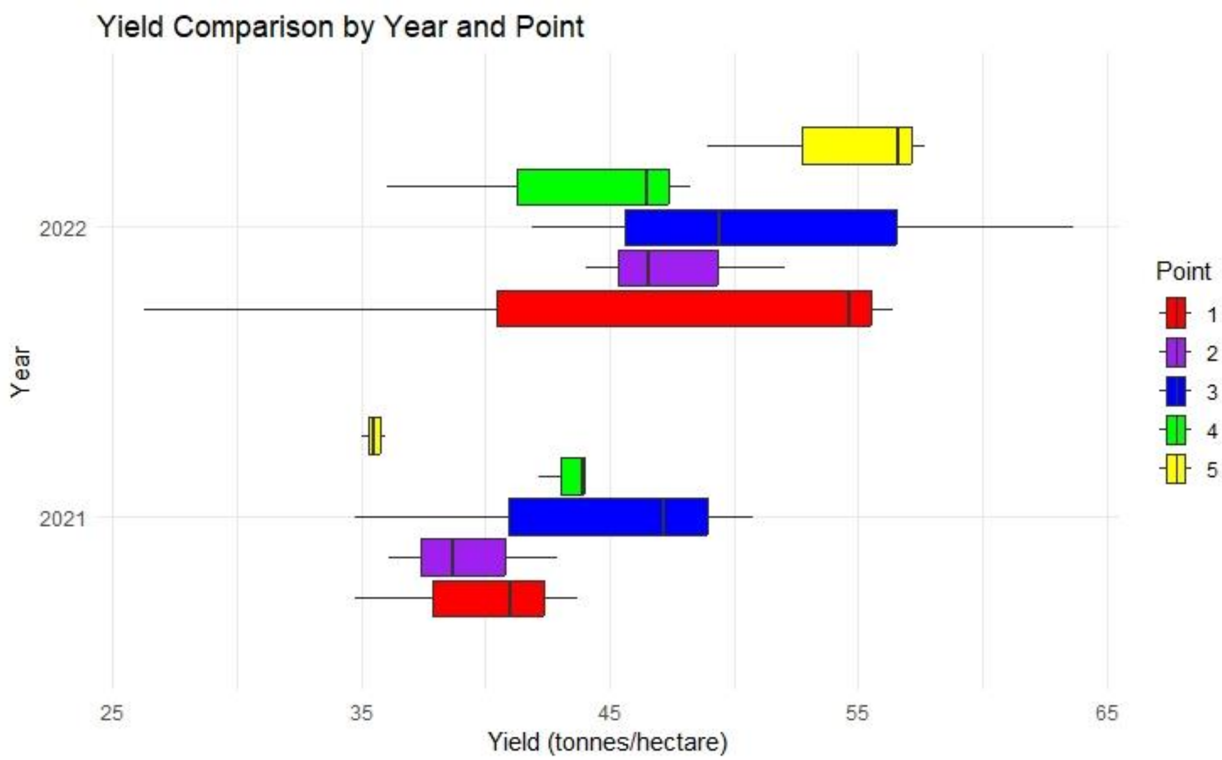


Fig. 4.9 Potato tuber yield at each transect point in the 2021 and 2022 fields.

In 2021, the mean potato yield across the transect was 40.4 tonnes/hectare, and in 2022 it was 48.6 tonnes/hectare. The median of the yield also increased from 41 tonnes/hectare in 2021 to 48.9 tonnes/hectare in 2022. The standard deviation increased from 5.04 tonnes/hectare in 2021 to 9.3 tonnes/hectare in 2022, suggesting greater variability in potato yield for the latter year. The coefficient of variation (CV), expressed as a percentage, followed this pattern, with the CV rising from 12.5% in 2021 to 19.2% in 2022 (Table 4.4).

Table 4.4 Mean, median, standard deviation, and coefficient of variation of the yields in tonnes/ha for each of the two years, 2021 and 2022.

	2021	**2022**
Mean	40.4	48.6
Median	41	48.9
Standard Deviation	5.04	9.3
Coefficient of variation	12.5	19.2

The lower yield in 2021 is likely a result of the heat dome event. The negative impact of unusually high temperature has been seen in other studies (Wagg et al., 2021) showing the resulting heat induced stress that affected the tubers physiological development resulting in a reduced yield.

Water use efficiency was calculated for each point, considering the variable rates of irrigation applied, and the final yields (Fig. 4.10). In 2022, the average WUE across all points was 9.79 KG/Ha/mm, with individual WUE values ranging from 5.61 KG/Ha/mm to 13.61 KG/Ha/mm. In 2021, the average WUE was slightly lower at 9.47 KG/Ha/mm, with individual WUE values ranging from 8.46 KG/Ha/mm to 13.68 KG/Ha/mm across the transect. The depression (valley) transect point in 2021 had the highest WUE value of 11.9 KG/Ha/mm, and in 2022 had a higher value than all but one hilltop point of 11.04 KG/Ha/mm showing a consistent, efficient use of water in depression areas. The WUE differences between points and years may be attributed to soil fertility, rooting system development differences among transect points and weather changes, especially colder night-time temperatures (Machakaire et al., 2023).

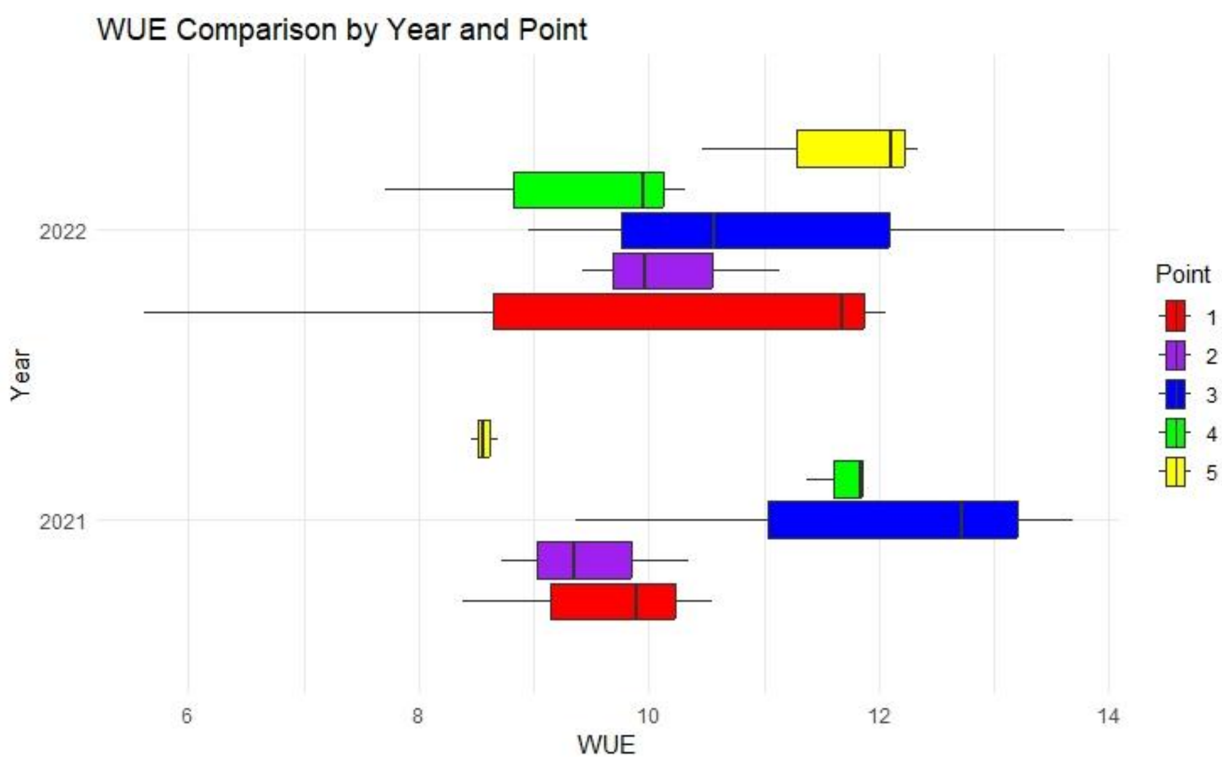


Fig. 4.10 Water use efficiency measured at each transect point throughout the 2021 and 2022 growing seasons.

The relationship between soil moisture and crop yield was analysed using separate linear regression models constructed for each year and moisture level (Fig. 4.11). For the year 2021, the model assessing the impact of moisture at 50% of the root zone revealed no significant effect on crop yield ($p = 0.98$). The model's low R-squared value (0.00031) indicated a poor fit. In contrast, for the year 2022, the relationship between the moisture and yield in the upper 50% of the effective root zone (ERZ) was more pronounced. Although not statistically significant ($p = 0.199$), the model showed a higher R-squared value (0.4736), suggesting a stronger linear relationship between soil moisture and crop yield. When looking at the soil moisture within 100% of the ERZ, neither the year 2021 nor 2022 exhibited a significant impact on crop yield, with p-values of 0.6591 and 0.4045, respectively. Both models displayed low R-squared values, indicating limited variance in crop yield explained by moisture levels. This is explained by soil moisture levels falling in a narrow range close to FC (100% available water), and above the allowable depletion level of 65% available water through the use of VRI across the transect.

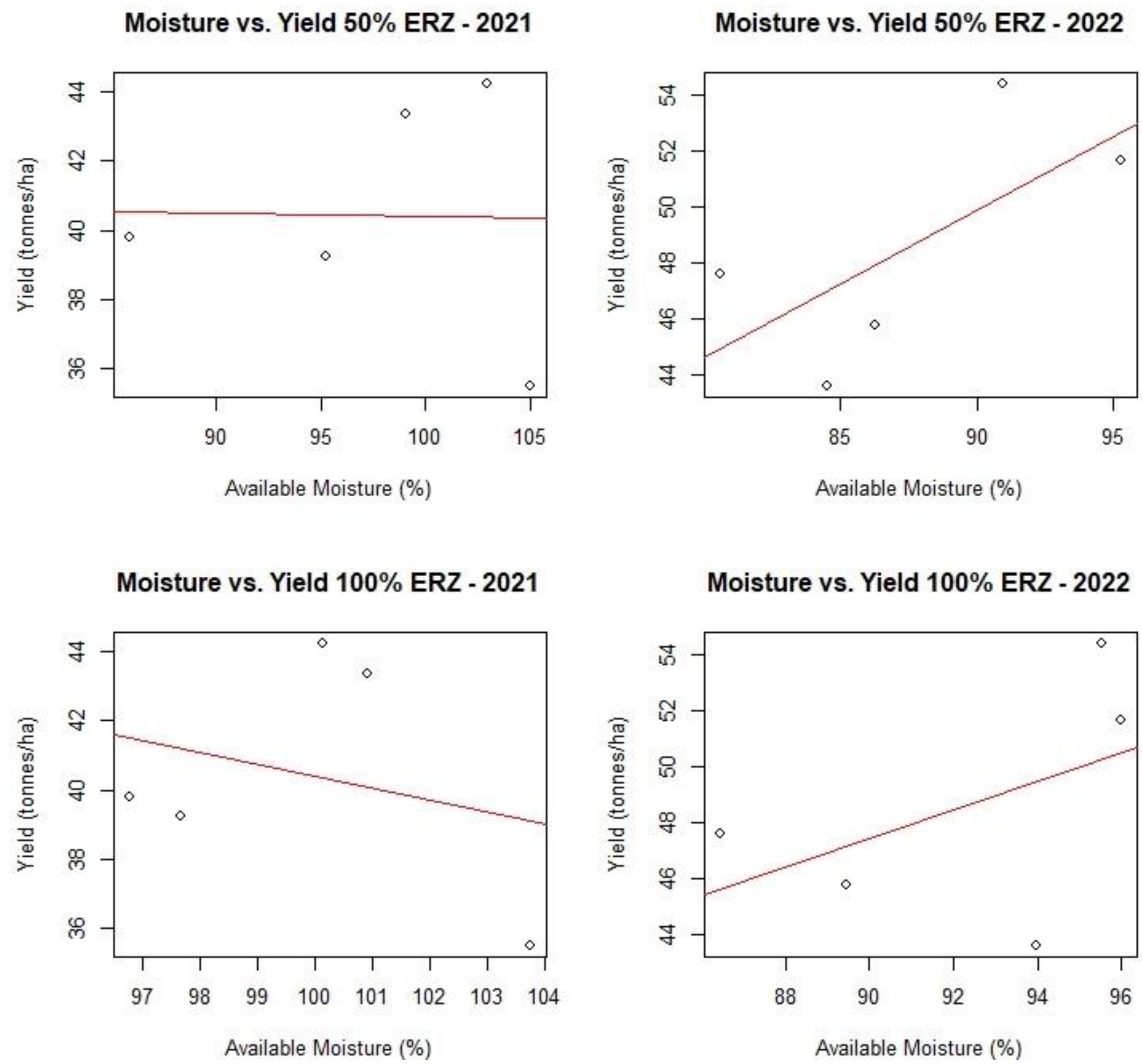


Fig 4.11 Linear relationships for 0-50% of the ERZ and 0-100% of the ERZ for 2021 and 2022 indicating the nature of the effect that Available Moisture had on Yield in tonnes/ha.

The precise delivery of irrigation using VRI based on real-time data and soil moisture measurements allowed for a uniform distribution of soil moisture across the entire field but had no significant effect on yield due to moisture distribution. To conserve water, VRI applications aimed to meet the crop needs while staying within the allowable depletion level set for the crop of 65% AM. Despite moisture levels going outside that range in 2021, the effect on overall yield was minimal. In 2022, though it stayed within that range, there was a trend towards positive relationship between moisture levels and yield, though again the relationship was not statistically significant. Water savings were realized through VRI. In 2021, the points receiving lower rates received a total of 51 mm less of irrigation applied, which would equate to approximately 251 000 total gallons of water saved within the area with the reduced rate in 2021. In 2022 the rate was uniform across the transect, and the entire transect received the same rate.

A similar study done by Matteau et al. (2022), used precision irrigation to maintain soil moistures within a specific range in a temporally variable field to determine effect on yield and water productivity. They found an increased yield in the years that they were more effectively able to manage soil moisture within their irrigation threshold. They found that potato yields were more likely to be reduced with excessive water application than deficits. They were also able to achieve significant water savings through a more targeted irrigation approach. Our study also demonstrated higher yields in the year that our soil moisture remained within our allowable depletion as well as water savings using precision methods. A study done by Badr et al. (2022) also looked at how water savings could be achieved, and they found they were able to achieve water savings especially in the later part of the growing season without a significant reduction in yields. Another study done by Camargo et al. (2015) found that crop yields significantly reduced both with under application and an over application of irrigation in a semi-arid region and noted a decreased water use efficiency with higher irrigation amounts.

4.5.5 Predictive Irrigation

The Alberta Irrigation Management Model (AIMM) was utilized to monitor soil moisture levels during each growing season and generate estimated soil moisture and irrigation predictions for two scenarios (AIMM alone and AIMM+ neutron probe (NP) monitoring). Both scenarios were initialized with the same soil moisture data for their starting point. The first scenario was run without any corrections during the season (AIMM), while the second scenario was corrected weekly based on neutron probe measurements (AIMMNP). Variable rates of irrigation were added for the appropriate monitoring points within the model. Moisture values were predicted and averaged for the upper 50% of the root zone (0-30cm) and the entire root zone (0-60cm) for 2021 (Fig. 4.12) and 2022 (Fig. 4.13). Throughout most of the season, higher soil moisture levels were observed for AIMM+NP. Both methods produce similar results for the first week where the two values are identical as expected. However, throughout the rest of the season the values predicted by AIMM without any correction are consistently lower with fluctuating levels of variance. Differences between methods in the upper half of the root zone vary from point to point, with similar peaks and valleys, and varying differences throughout the season. This is the result of VRI being implemented through varying application size, not varying application frequency. When considering the entire root zone, similar trends are apparent. However, as the season progressed the difference between methods progressively increased. Predicted soil moisture values in 2022 showed similar trends those seen in 2021, with less variation between the two methods, particularly when looking at the upper half of the rooting zone. Similarly, in 2022 there was an increasing divergence in the values as the season progressed when looking at the entire root zone.

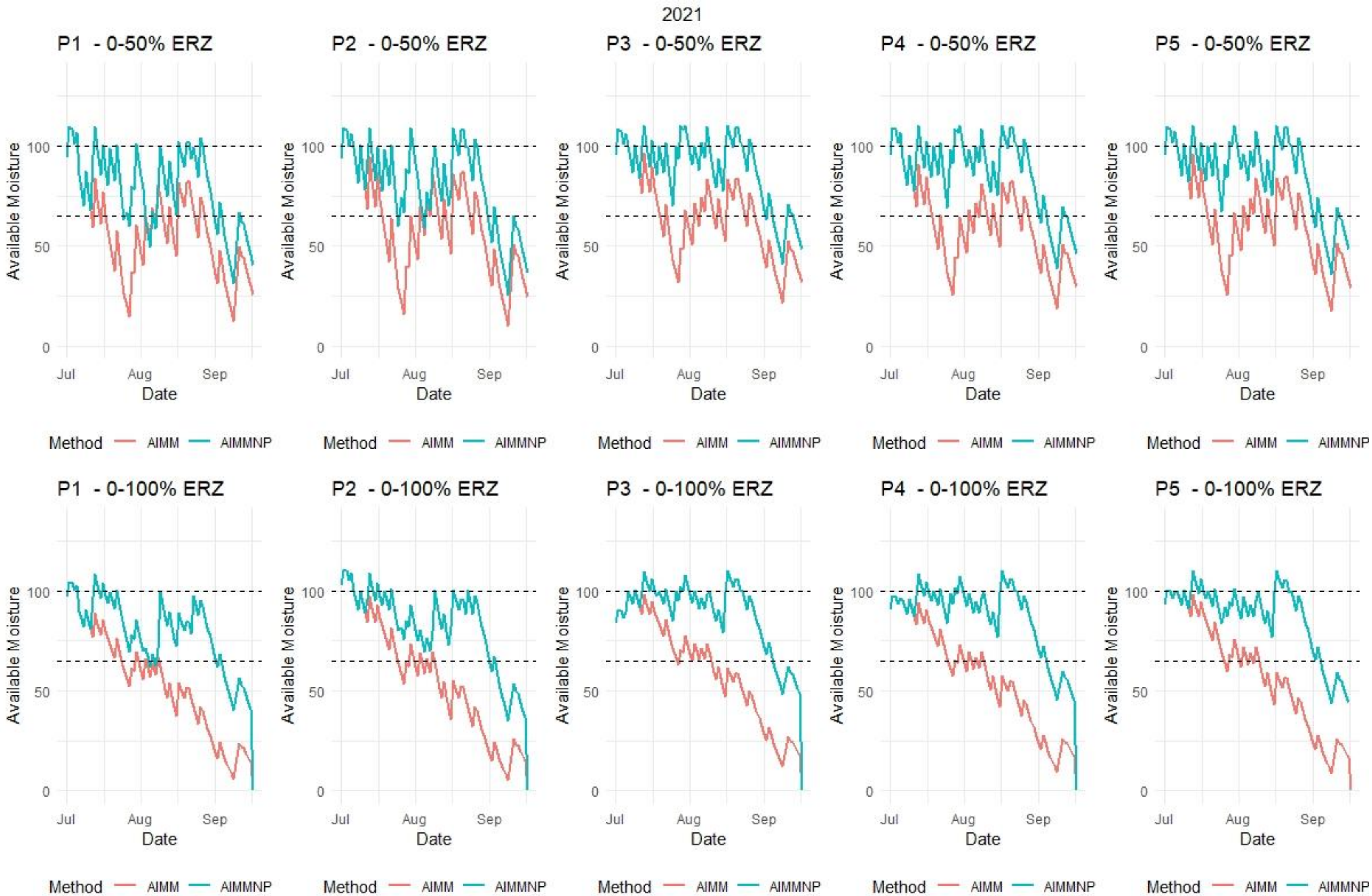


Fig. 4.12 Comparison of Available Moisture over the 2021 growing season for different points (P1 to P5) using AIMM predictions without corrections and AIMM corrected weekly using neutron probe measurements. Plots include data from two profile, representing Available Moisture in the 0-50% and 0-100% of the ERZ (Effective Root Zone).

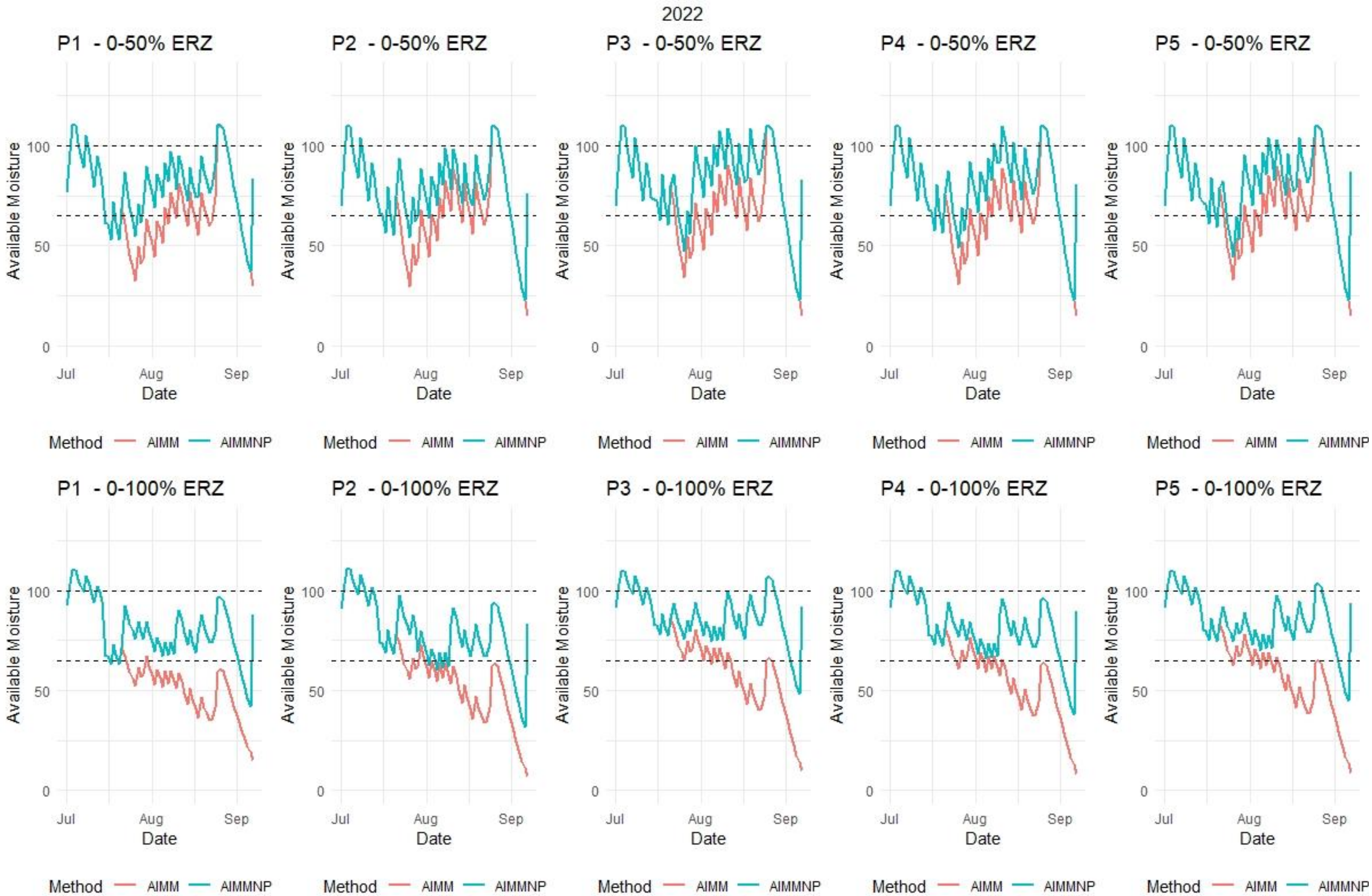


Fig. 4.13 Comparison of Available Moisture over the 2021 growing Season for different points (P1 to P5) using AIMM predictions without corrections and AIMM corrected weekly using neutron probe measurements. Plots include data from two profile, representing Available Moisture in the 0-50% and 0-100% of the ERZ (Effective Root Zone).

The model's performance was evaluated by calculating the Nash-Sutcliffe Efficiency (NSE) in the 50% and 100% of the ERZ for each year, using the AIMM + NP model as the true condition. In 2021, the NSE values for AIMM alone were poor, reaching -1 for 0-50% of the ERZ and -3.6 for 0-100% of the ERZ. These negative NSE values in 2021 indicate poor model performance, suggesting that the predictions were not aligned with the observed soil moisture dynamics and, in some cases, were worse than a simple mean. The AIMM prediction model showed a significant improvement in 2022, with NSE values of 0.9 for 0-50% of the ERZ and 0.8 for 0-100% of the ERZ. These positive NSE values in 2022 suggest a closer alignment between the predicted and observed values, signifying improved accuracy. The better performance in 2022 is indicated by the values approaching 1, showing a higher degree of accuracy, especially in 0-50% of the ERZ. The results indicate that AIMM demonstrated more reliable predictive capabilities in capturing soil moisture variations, particularly in shallower soil depths during 2022.

The Root Mean Square Error (RMSE) was also used to evaluate the performance of the AIMM model. In 2021, AIMM had higher RMSE values of 19.8 for 0-50% of the ERZ and 23.6 for 0-100% of the ERZ. These high RMSE values suggest a larger average prediction error, indicating a less accurate representation of observed soil moisture. However, in 2022, there was an improvement in model performance. The RMSE values decreased to 10 for 0-50% of the ERZ and 16.6 for 0-100% of the ERZ. These lower RMSE values indicate a more accurate prediction of soil moisture levels, reflecting improved performance by AIMM in predicting soil moisture variability. The difference observed in RMSE values between the two years underlines the importance of various variables that can impact model performance from year to year and influence the model's reliability.

The variability seen in the performance of AIMM over the two years of this study can be affected by a variety of factors. Soil organic matter, bulk density of the soil, soil texture, weather, topography, subsoil constraints all would have played a role in the performance of AIMM. Although AIMM offers ability to manually input soil texture data, one cannot fine tune percentages of sand, silt, and clay within that textural group. This can result in a different water holding capacity and the larger the difference, the less accurate the model will be able to predict. Model reliability could be improved with the ability to add in more precise values. The specific effect some weather patterns have on overall growth of potatoes can also play a role in predictions. The higher temperatures in 2021 would have played a role in crop development and the associated lower yields seen in that year. It is probable that the Kc function in AIMM was not representative for these conditions, and where they occurred in the growth cycle. AIMM also has no method to account for detailed hydrological processes in or beneath the rootzone. Drainage is expected to happen instantaneously and no capillary effects from groundwater are considered. This may explain a poorer performance in 100% depth models versus 50% depth. AIMM has no way to account for agronomic practices that can affect crop growth either. Agronomic management practices can cause crop growth and development to track outside of the values the model calculates, which can result in inaccurate predictions of soil moisture. To account for these differences, it is important to pair the use of AIMM with field monitoring, to correct for the discrepancies in model performance. This will allow for accurate predictions and adjust for differences caused by agronomic practices, microsite differences, and other variables that cannot be accounted for using this software. Understanding and accounting for factors that affect model performance are crucial for utilizing this method to tailor irrigation practices to the specific needs of the crops and the field, optimizing water utilization.

Irrigation management is often a challenge for farmers, accounting for the many variables that can affect soil moisture across different fields and from year to year. Crops that have high sensitivity to water stress such as potatoes can add even more intensity in the level of management required to meet the crops needs. Using predictive Irrigation scheduling systems offers farmers a way to use data analytics, remote sensing, and meteorological models to predict optimal water requirements of their crops. These models analyse crop water requirements, weather data and soil moisture to make irrigation predictions ensuring irrigation applications meet crop needs without excessive water application (Ahmed Sharma, 2023). Predictive irrigation methods have been shown to improve water use efficiency, reduce water losses, and improve overall yield and quality of crops. One study done by Alibabaei et al. (2021) in Portugal, found that they could reduce water usage by up to 30% in potato crops using predictive methods of irrigation scheduling without losing yield or quality. When a region is facing water scarcity issues, the use of predictive irrigation systems can offer a valuable tool to minimize water usage without sacrificing yields and have been implemented in many regions across the world with promising results (Yartu et al. 2021). However, in southern Alberta, the uptake of precision techniques is still low. A study done by Nicol, Nicol (2021), surveyed farmers and found that the highest uptake of precision technologies was found in producers growing specialty crops, but that most had only adopted basic technologies such as sensors and VRI. They found that uptake of more advanced technologies is slower, often due to lack of knowledge, training required, and cost of equipment.

Although the use of predictive irrigation systems comes with many benefits, there are also many challenges. As indicted by the results in this study, the predictive model did not prove to be a reliable source for soil moisture predictions without the use of in field monitoring to adjust the model. Weekly in-field monitoring improved model predictions. Predictive systems rely on accurate data to make correct predictions, without which farmers may unknowingly make ineffective irrigation management decisions (Ahmed, Sharma, 2023). The AIMM predictive model relies on current and historical weather data from the weather stations in the IMCIN database, or weather data can be manually uploaded. Most farmers that would use this software would not have the knowledge on how to upload their own weather data, even if they had their own weather station, so they rely on data collected from the station closest to them. Precipitation can also be highly variable between AIMM values and field values but may be easily adjusted within the program. In many regions there is a lack of data and weather monitoring stations which can make it difficult for the model to make accurate predictions (Ahmed, Sharma 2023).

4.6 CONCLUSIONS

Efficient water management is essential to maintain sustainable agricultural production and address water scarcity challenges. This study examined patterns and controls on soil moisture, potato yield and water use efficiency in transects across VRI irrigated fields and assessed the effectiveness of the Alberta Irrigation Management Model (AIMM) in predicting soil moisture in a field irrigated by VRI. The AIM model had a considerable degree of variation from field observations when no adjustments to soil moisture were made, emphasizing the necessity for pairing models with field observations to make irrigation decisions. The relationship between yield and soil moisture was compared between monitoring points, and no significant relationship between yield and moisture was found, indicating success in the ability of predictive scheduling and VRI in removing this source of yield variability. When used correctly, predictive models such as AIMM integrated with field monitoring, can be a valuable tool to assist in real-time monitoring of soil moisture assisting in making appropriate irrigation management decisions throughout the growing season. This allows producers to make decisions based on measured soil moisture values in their fields, as well as a forecast for estimated water use within the next week. The use of VRI can assist producers in accounting for spatial and temporal variations throughout the field and maintain a more uniform soil moisture across their field, resulting in water savings without sacrificing yield. The use of AIMM with VRI allowed maintenance of soil moisture within the ideal range across the field with variations in topography. Though water is the main driver of potato yields and quality, it is also important to note that there are other factors not examined in this study that resulted in yield variations. Use of predictive models can be affected by many different factors, and the results presented in this study can offer a guide in using this technology most effectively and make informed decision to optimize crop yields and water utilization in agricultural systems.

5 Synthesis and Conclusions

With the growing water scarcity challenges it is important to find effective methods to utilize water resources more efficiently. Precision application of irrigation water that ensures the crop has the correct amount of soil available water at the correct time is an aid in addressing these challenges. The use of predictive irrigation scheduling, either with or without variable rate application technology, allows producers to take their irrigation management practices to the next level and begin accounting for the variables that affect soil moisture and crop water usage across their fields. Accounting for the temporal and spatial variability across their fields and adjusting irrigation practices accordingly while ensuring crop needs are met across the landscape will allow for increased water use efficiencies to be achieved while preserving potato yields and qualities.

There are many tools available to farmers that will allow informed irrigation management decisions, including use of soil moisture monitoring sensors in combination with predictive models such as AIMM and technology like VRI pivot systems. Their use can allow producers to track crop water use and moisture conditions throughout a season and predict when irrigations will be needed and adjust accordingly. This allows a proactive approach to irrigation scheduling and helps limit water stress on the crop. In this thesis research work, the study described in chapter 3 investigated the use of precision irrigation on five farmer fields across southern Alberta. These fields contained a wide range of topographical and soil conditions, and represented the entire region where irrigated potatoes are grown in southern Alberta. The purpose of this observational study was to first assess and understand the impact of topography, soil, and weather on potato yield. This was evaluated by assessing the cumulative effect of these variables over 4 growing seasons. In chapter 4 this understanding was then used to examine controls on soil available water in transects across VRI irrigated fields and performance of predictive irrigation scheduling using AIMM with and without inputted in-field neutron probe soil moisture data. The ability to predict soil moisture with AIMM in combination with VRI was a successful approach in producing a uniform soil moisture condition throughout fields with variable topography that reduced the impact on soil moisture differences on end yield.

5.1 SUMMARY OF FINDINGS

In the research analysis in Chapter 3, the focus was on assessing in-field variability, including soil texture, soil complexity index, and topography complexity, and their influence on soil moisture dynamics impacting potato yield. Actual potato producer fields used in this study exhibited variations in soil complexity and topographical complexities, with no strong correlation between them. Weather conditions, particularly temperature variations and the occurrence of a "heat dome" event in 2021, greatly influenced potato growth and tuber development. Soil moisture levels across potato fields over the growing season were monitored and averaged for two stages of potato growth—tuber initiation and tuber bulking. The coefficient of variation (CV) was calculated for available moisture during these growth stages, with generally higher variability in the 0-35 cm depths where potatoes extract most of their water. The variability in potato yield across fields was also investigated between sites, and years, attributing variations to factors such as soil properties, soil available moisture levels, and external weather conditions. The coefficient of variation for total and marketable yield varied across sites and years, with precision irrigation methods identified as a potential tool to enhance and produce more consistent yields by accounting for influencing factors on soil moisture.

A comprehensive investigation was conducted on the factors influencing potato yield, particularly focusing on available moisture during tuber initiation and tuber bulking, topography complexity, growing degree days (GDD), and soil complexity. Eight linear mixed-effects models were used to analyze the relationships between these factors and total yield as well as marketable potato yield during tuber initiation and tuber bulking stages. The results revealed varying levels of significance across models, with soil moisture having a significant impact on both total and marketable yield during tuber bulking. Topography, particularly non-flat terrain, demonstrated a consistently negative effect on yield, emphasizing the importance of considering influence of topographic features in potato production. However, GDD and soil complexity exhibited inconsistent significance. The study contributes to the understanding of factors affecting potato yield and suggests that precision irrigation management, considering soil available moisture, soil complexity, and topography, can play an important part in optimizing yield.

The study presented in chapter 4 assessed the utility of a predictive irrigation software called AIMM in conjunction with Variable Rate Irrigation (VRI) to address variable soil moisture as a limitation. Soil moisture level predictions from the AIMM model were monitored using just the software, as well as using the base predictions and adjusting moisture weekly using a neutron probe data as input. Soil moisture data collected using the neutron probe displayed variable patterns across the seasons, with 2021 showing higher variation and 2022 exhibiting more consistent soil moisture. Weather also played a role in differences between the 2 years with a "heat dome" effect in 2021 leading to higher temperatures and higher GDD. Lower rainfall was also noted in 2021. The investigation into potato yield variations across the transect and years revealed an increase from 40.4 to 48.6 tonnes/hectare between 2021 and 2022. WUE also demonstrated a slight increase from 9.47 in 2021 to 9.79 in 2022. The study explored the relationship between soil moisture and crop yield, revealing a non-significant relationship between moisture and yield, with water savings. Uniformity of soil moisture and maintenance in the “optimum” range across fields of variable topography was achieved with the precision approach of AIMM and VRI. The use of predictive models such as the Alberta Irrigation Management Model (AIMM) with in-field monitoring showed promise, acting as a valuable tool for real-time monitoring and management of soil moisture levels. Many variables must be considered when using these models, and their success is based on accurate and timely data.

5.2 SUGGESTED METHOD IMPROVEMENTS AND FUTURE RESEARCH DIRECTION

Various areas were noted in terms of potential improvement while evaluating the use of precision irrigation.

(1) A replicated trial with different irrigation treatments on the different areas of variability, with a control treatment within each field, would have provided interesting information and contributed to the strength of documentation of the differences that could be achieved.

(2) More targeted research could also be done comparing fields with less variables differing. For example, use multiple potato fields owned and managed by the same farmer to reduce influence of management differences between sites.

(3) Ensuring that all other management practices such as fertilizer, seeding, hilling, and pesticide treatments etc. are comparable between farms and not impacting the final yields.

The determination of variable rate prescriptions represents a significant challenge for many producers. Further research is needed to provide producers with the knowledge required to adjust application rates and build prescriptions based on the variability that can be observed within their fields. A more comprehensive grasp of the variables most likely to influence soil moisture and the calculation of a specific rate is required.

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Appendix 1: Additional Available Moisture Data

Table A1.1. Percentage Available Moisture for Farms F1-F5 from 2019-2022

				0-35 cm		35-60 cm	
Year	**Farm**	**Field**	**Site**	**AM Tuber Initiation**	**AM Tuber Bulking**	**AM Tuber Initiation**	**AM Tuber Bulking**
2022	F1	F122	F122P1	91.4	66.6	98.3	76.5
2022	F1	F122	F122P1	91.4	66.6	98.3	76.5
2022	F1	F122	F122P1	91.4	66.6	98.3	76.5
2022	F1	F122	F122P2	85.6	87.6	98.8	89.7
2022	F1	F122	F122P2	85.6	87.6	98.8	89.7
2022	F1	F122	F122P2	85.6	87.6	98.8	89.7
2022	F1	F122	F122P3	94.9	73.9	90.2	96.9
2022	F1	F122	F122P3	94.9	73.9	90.2	96.9
2022	F1	F122	F122P3	94.9	73.9	90.2	96.9
2022	F1	F122	F122P4	89.4	70.7	89	96.6
2022	F1	F122	F122P4	89.4	70.7	89	96.6
2022	F1	F122	F122P4	89.4	70.7	89	96.6
2022	F1	F122	F122P5	72.2	72.6	95	91.8
2022	F1	F122	F122P5	72.2	72.6	95	91.8
2022	F1	F122	F122P5	72.2	72.6	95	91.8
2022	F1	F122	F122P6	70	72.9	95	91.4
2022	F1	F122	F122P6	70	72.9	95	91.4
2022	F1	F122	F122P6	70	72.9	95	91.4
2022	F2	F222	F222P1	99.4	74.7	85.4	93.4
2022	F2	F222	F222P1	99.4	74.7	85.4	93.4
2022	F2	F222	F222P1	99.4	74.7	85.4	93.4
2022	F2	F222	F222P2	102.4	81.3	92.9	98
2022	F2	F222	F222P2	102.4	81.3	92.9	98
2022	F2	F222	F222P2	102.4	81.3	92.9	98
2022	F2	F222	F222P3	94.3	66.9	91.3	88.4
2022	F2	F222	F222P3	94.3	66.9	91.3	88.4
2022	F2	F222	F222P3	94.3	66.9	91.3	88.4
2022	F2	F222	F222P4	98	83.1	92.8	91.8
2022	F2	F222	F222P4	98	83.1	92.8	91.8
2022	F2	F222	F222P4	98	83.1	92.8	91.8
2022	F2	F222	F222P5	80.8	81.6	90.9	84.2
2022	F2	F222	F222P5	80.8	81.6	90.9	84.2
2022	F2	F222	F222P5	80.8	81.6	90.9	84.2
2022	F2	F222	F222P6	110.9	101.8	97.1	97.7
2022	F2	F222	F222P6	110.9	101.8	97.1	97.7
2022	F2	F222	F222P6	110.9	101.8	97.1	97.7

2022	F3	F322	F322P1	95.8	92.8	94.2	93.3
2022	F3	F322	F322P1	95.8	92.8	94.2	93.3
2022	F3	F322	F322P1	95.8	92.8	94.2	93.3
2022	F3	F322	F322P2	84.7	91.8	81.5	94.9
2022	F3	F322	F322P2	84.7	91.8	81.5	94.9
2022	F3	F322	F322P2	84.7	91.8	81.5	94.9
2022	F3	F322	F322P3	87.7	87.3	93.5	98.2
2022	F3	F322	F322P3	87.7	87.3	93.5	98.2
2022	F3	F322	F322P3	87.7	87.3	93.5	98.2
2022	F3	F322	F322P4	98.1	89.2	111.5	109.5
2022	F3	F322	F322P4	98.1	89.2	111.5	109.5
2022	F3	F322	F322P4	98.1	89.2	111.5	109.5
2022	F3	F322	F322P5	78.8	93.1	93.6	98
2022	F3	F322	F322P5	78.8	93.1	93.6	98
2022	F3	F322	F322P5	78.8	93.1	93.6	98
2022	F3	F322	F322P6	95.4	91.7	95.4	98.7
2022	F3	F322	F322P6	95.4	91.7	95.4	98.7
2022	F3	F322	F322P6	95.4	91.7	95.4	98.7
2022	F4	F422	F422P1	74.1	69.5	73.5	58
2022	F4	F422	F422P1	74.1	69.5	73.5	58
2022	F4	F422	F422P1	74.1	69.5	73.5	58
2022	F4	F422	F422P2	90.8	88.6	70.7	79
2022	F4	F422	F422P2	90.8	88.6	70.7	79
2022	F4	F422	F422P2	90.8	88.6	70.7	79
2022	F4	F422	F422P3	90.5	76.4	81.4	73.2
2022	F4	F422	F422P3	90.5	76.4	81.4	73.2
2022	F4	F422	F422P3	90.5	76.4	81.4	73.2
2022	F4	F422	F422P4	79.9	81.9	89.2	94.2
2022	F4	F422	F422P4	79.9	81.9	89.2	94.2
2022	F4	F422	F422P4	79.9	81.9	89.2	94.2
2022	F4	F422	F422P5	76.5	76.9	94.7	96.4
2022	F4	F422	F422P5	76.5	76.9	94.7	96.4
2022	F4	F422	F422P5	76.5	76.9	94.7	96.4
2022	F4	F422	F422P6	62.1	60.5	99.7	100.2
2022	F4	F422	F422P6	62.1	60.5	99.7	100.2
2022	F4	F422	F422P6	62.1	60.5	99.7	100.2
2021	F1	F121	F121P1	99	65.1	97.5	91.3
2021	F1	F121	F121P1	99	65.1	97.5	91.3
2021	F1	F121	F121P1	99	65.1	97.5	91.3
2021	F1	F121	F121P2	89.7	73.3	89.3	70
2021	F1	F121	F121P2	89.7	73.3	89.3	70
2021	F1	F121	F121P2	89.7	73.3	89.3	70
2021	F1	F121	F121P3	74.1	65.7	96.3	77.7
2021	F1	F121	F121P3	74.1	65.7	96.3	77.7

2021	F1	F121	F121P3	74.1	65.7	96.3	77.7
2021	F1	F121	F121P4	99.5	72	97.9	79.7
2021	F1	F121	F121P4	99.5	72	97.9	79.7
2021	F1	F121	F121P4	99.5	72	97.9	79.7
2021	F1	F121	F121P5	94.3	59.8	100.3	81.1
2021	F1	F121	F121P5	94.3	59.8	100.3	81.1
2021	F1	F121	F121P5	94.3	59.8	100.3	81.1
2021	F2	F221	F222P1	86	79.8	81.8	75.7
2021	F2	F221	F222P1	86	79.8	81.8	75.7
2021	F2	F221	F222P1	86	79.8	81.8	75.7
2021	F2	F221	F222P2	86.7	62	86.7	62
2021	F2	F221	F222P2	86.7	62	86.7	62
2021	F2	F221	F222P2	86.7	62	86.7	62
2021	F2	F221	F222P3	95.8	72.5	94.5	71.3
2021	F2	F221	F222P3	95.8	72.5	94.5	71.3
2021	F2	F221	F222P3	95.8	72.5	94.5	71.3
2021	F2	F221	F222P4	75.8	59.1	80.2	63.1
2021	F2	F221	F222P4	75.8	59.1	80.2	63.1
2021	F2	F221	F222P4	75.8	59.1	80.2	63.1
2021	F2	F221	F222P5	87.3	77.6	90.4	80.5
2021	F2	F221	F222P5	87.3	77.6	90.4	80.5
2021	F2	F221	F222P5	87.3	77.6	90.4	80.5
2021	F2	F221	F222P6	97.4	62.3	95.1	94.9
2021	F2	F221	F222P6	97.4	62.3	95.1	94.9
2021	F2	F221	F222P6	97.4	62.3	95.1	94.9
2021	F3	F321	F321P1	88.8	83.6	92.5	97.8
2021	F3	F321	F321P1	88.8	83.6	92.5	97.8
2021	F3	F321	F321P1	88.8	83.6	92.5	97.8
2021	F3	F321	F321P2	44.6	82.9	70.3	91.5
2021	F3	F321	F321P2	44.6	82.9	70.3	91.5
2021	F3	F321	F321P2	44.6	82.9	70.3	91.5
2021	F3	F321	F321P3	85.5	83.8	90.7	96.1
2021	F3	F321	F321P3	85.5	83.8	90.7	96.1
2021	F3	F321	F321P3	85.5	83.8	90.7	96.1
2021	F3	F321	F321P4	79.9	85	95.2	99.4
2021	F3	F321	F321P4	79.9	85	95.2	99.4
2021	F3	F321	F321P4	79.9	85	95.2	99.4
2021	F3	F321	F321P5	62.2	82.7	92.9	98.2
2021	F3	F321	F321P5	62.2	82.7	92.9	98.2
2021	F3	F321	F321P5	62.2	82.7	92.9	98.2
2021	F4	F421	F421P1	97.3	94.5	97.3	94.5
2021	F4	F421	F421P1	97.3	94.5	97.3	94.5
2021	F4	F421	F421P1	97.3	94.5	97.3	94.5
2021	F4	F421	F421P2	95.2	96.2	95.2	96.2

2021	F4	F421	F421P2	95.2	96.2	95.2	96.2
2021	F4	F421	F421P2	95.2	96.2	95.2	96.2
2021	F4	F421	F421P3	90	73.7	90	73.7
2021	F4	F421	F421P3	90	73.7	90	73.7
2021	F4	F421	F421P3	90	73.7	90	73.7
2021	F4	F421	F421P4	92	94	92	94
2021	F4	F421	F421P4	92	94	92	94
2021	F4	F421	F421P4	92	94	92	94
2021	F4	F421	F421P5	98.2	96.9	98.2	96.9
2021	F4	F421	F421P5	98.2	96.9	98.2	96.9
2021	F4	F421	F421P5	98.2	96.9	98.2	96.9
2021	F5	F521	F521P1	82.4	87	99	85.3
2021	F5	F521	F521P1	82.4	87	99	85.3
2021	F5	F521	F521P1	82.4	87	99	85.3
2021	F5	F521	F521P2	96.5	77.8	95.7	93.5
2021	F5	F521	F521P2	96.5	77.8	95.7	93.5
2021	F5	F521	F521P2	96.5	77.8	95.7	93.5
2021	F5	F521	F521P3	99.8	72.1	139.4	89.8
2021	F5	F521	F521P3	99.8	72.1	139.4	89.8
2021	F5	F521	F521P3	99.8	72.1	139.4	89.8
2021	F5	F521	F521P4	88.9	87.2	91.5	92.7
2021	F5	F521	F521P4	88.9	87.2	91.5	92.7
2021	F5	F521	F521P4	88.9	87.2	91.5	92.7
2021	F5	F521	F521P5	85.2	79.6	99.8	96.4
2021	F5	F521	F521P5	85.2	79.6	99.8	96.4
2021	F5	F521	F521P5	85.2	79.6	99.8	96.4
2020	F1	F120	F120P1	59.6	85.1	98.7	76.1
2020	F1	F120	F120P1	59.6	85.1	98.7	76.1
2020	F1	F120	F120P1	59.6	85.1	98.7	76.1
2020	F1	F120	F120P2	91.5	81.7	97.4	85.8
2020	F1	F120	F120P2	91.5	81.7	97.4	85.8
2020	F1	F120	F120P2	91.5	81.7	97.4	85.8
2020	F1	F120	F120P3	94.5	82.7	97.4	84.8
2020	F1	F120	F120P3	94.5	82.7	97.4	84.8
2020	F1	F120	F120P3	94.5	82.7	97.4	84.8
2020	F1	F120	F120P4	84.7	69.8	95	96.2
2020	F1	F120	F120P4	84.7	69.8	95	96.2
2020	F1	F120	F120P4	84.7	69.8	95	96.2
2020	F1	F120	F120P5	72.1	82.7	98.7	98.1
2020	F1	F120	F120P5	72.1	82.7	98.7	98.1
2020	F1	F120	F120P5	72.1	82.7	98.7	98.1
2020	F2	F220	F220P1	76	43.5	92	78.3
2020	F2	F220	F220P1	76	43.5	92	78.3
2020	F2	F220	F220P1	76	43.5	92	78.3

2020	F2	F220	F220P2	60.4	38.7	92.9	92.9
2020	F2	F220	F220P2	60.4	38.7	92.9	92.9
2020	F2	F220	F220P2	60.4	38.7	92.9	92.9
2020	F2	F220	F220P3	56.9	71.6	97.2	94.2
2020	F2	F220	F220P3	56.9	71.6	97.2	94.2
2020	F2	F220	F220P3	56.9	71.6	97.2	94.2
2020	F2	F220	F220P4	85.4	46.8	83.1	67.4
2020	F2	F220	F220P4	85.4	46.8	83.1	67.4
2020	F2	F220	F220P4	85.4	46.8	83.1	67.4
2020	F2	F220	F220P5	52.9	65.1	84.1	85.7
2020	F2	F220	F220P5	52.9	65.1	84.1	85.7
2020	F2	F220	F220P5	52.9	65.1	84.1	85.7
2020	F3	F320	F320P1	63.1	77.9	84.1	89.2
2020	F3	F320	F320P1	63.1	77.9	84.1	89.2
2020	F3	F320	F320P1	63.1	77.9	84.1	89.2
2020	F3	F320	F320P2	55.3	72.3	92	98.2
2020	F3	F320	F320P2	55.3	72.3	92	98.2
2020	F3	F320	F320P2	55.3	72.3	92	98.2
2020	F3	F320	F320P3	67	85.6	89.7	93.3
2020	F3	F320	F320P3	67	85.6	89.7	93.3
2020	F3	F320	F320P3	67	85.6	89.7	93.3
2020	F3	F320	F320P4	75	89.4	85.5	66.6
2020	F3	F320	F320P4	75	89.4	85.5	66.6
2020	F3	F320	F320P4	75	89.4	85.5	66.6
2020	F3	F320	F320P5	82.1	79.1	95	97.9
2020	F3	F320	F320P5	82.1	79.1	95	97.9
2020	F3	F320	F320P5	82.1	79.1	95	97.9
2020	F4	F420	F420P1	74	82	82.1	98.3
2020	F4	F420	F420P1	74	82	82.1	98.3
2020	F4	F420	F420P1	74	82	82.1	98.3
2020	F4	F420	F420P2	87.4	75.6	89	93.7
2020	F4	F420	F420P2	87.4	75.6	89	93.7
2020	F4	F420	F420P2	87.4	75.6	89	93.7
2020	F4	F420	F420P3	61.1	86.9	88.6	96.9
2020	F4	F420	F420P3	61.1	86.9	88.6	96.9
2020	F4	F420	F420P3	61.1	86.9	88.6	96.9
2020	F4	F420	F420P4	93.2	78.9	92.2	93.1
2020	F4	F420	F420P4	93.2	78.9	92.2	93.1
2020	F4	F420	F420P4	93.2	78.9	92.2	93.1
2020	F4	F420	F420P5	94.2	69.9	87.4	92.2
2020	F4	F420	F420P5	94.2	69.9	87.4	92.2
2020	F4	F420	F420P5	94.2	69.9	87.4	92.2
2020	F5	F520	F520P1	77	88.4	91.9	97.9
2020	F5	F520	F520P1	77	88.4	91.9	97.9

2020	F5	F520	F520P1	77	88.4	91.9	97.9
2020	F5	F520	F520P2	105.7	81.3	97.2	95.4
2020	F5	F520	F520P2	105.7	81.3	97.2	95.4
2020	F5	F520	F520P2	105.7	81.3	97.2	95.4
2020	F5	F520	F520P3	92.1	80.1	81.2	87.7
2020	F5	F520	F520P3	92.1	80.1	81.2	87.7
2020	F5	F520	F520P3	92.1	80.1	81.2	87.7
2020	F5	F520	F520P4	86.5	88.1	101	89
2020	F5	F520	F520P4	86.5	88.1	101	89
2020	F5	F520	F520P4	86.5	88.1	101	89
2020	F5	F520	F520P5	97.4	69.6	97	93.7
2020	F5	F520	F520P5	97.4	69.6	97	93.7
2020	F5	F520	F520P5	97.4	69.6	97	93.7
2019	F1	F119	F119P1	88.3	80.4	95.9	98.4
2019	F1	F119	F119P1	88.3	80.4	95.9	98.4
2019	F1	F119	F119P1	88.3	80.4	95.9	98.4
2019	F1	F119	F119P2	84	85.2	93.7	94
2019	F1	F119	F119P2	84	85.2	93.7	94
2019	F1	F119	F119P2	84	85.2	93.7	94
2019	F1	F119	F119P3	88	68.2	94.6	93.7
2019	F1	F119	F119P3	88	68.2	94.6	93.7
2019	F1	F119	F119P3	88	68.2	94.6	93.7
2019	F1	F119	F119P4	85.7	83.1	86.5	91
2019	F1	F119	F119P4	85.7	83.1	86.5	91
2019	F1	F119	F119P4	85.7	83.1	86.5	91
2019	F1	F119	F119P5	86.8	81.9	92	89.2
2019	F1	F119	F119P5	86.8	81.9	92	89.2
2019	F1	F119	F119P5	86.8	81.9	92	89.2
2019	F2	F219	F219P1	46.8	87.7	72.6	89
2019	F2	F219	F219P1	46.8	87.7	72.6	89
2019	F2	F219	F219P1	46.8	87.7	72.6	89
2019	F2	F219	F219P2	59.2	83	93	96
2019	F2	F219	F219P2	59.2	83	93	96
2019	F2	F219	F219P2	59.2	83	93	96
2019	F2	F219	F219P3	54.9	93.6	69.7	82.4
2019	F2	F219	F219P3	54.9	93.6	69.7	82.4
2019	F2	F219	F219P3	54.9	93.6	69.7	82.4
2019	F2	F219	F219P4	64.8	89.1	81.7	92.9
2019	F2	F219	F219P4	64.8	89.1	81.7	92.9
2019	F2	F219	F219P4	64.8	89.1	81.7	92.9
2019	F2	F219	F219P5	46.7	81.7	85.7	90.5
2019	F2	F219	F219P5	46.7	81.7	85.7	90.5
2019	F2	F219	F219P5	46.7	81.7	85.7	90.5
2019	F3	F319	F319P1	53	80.2	92.3	94.2

2019	F3	F319	F319P1	53	80.2	92.3	94.2
2019	F3	F319	F319P1	53	80.2	92.3	94.2
2019	F3	F319	F319P2	58.6	82.8	80.3	83.4
2019	F3	F319	F319P2	58.6	82.8	80.3	83.4
2019	F3	F319	F319P2	58.6	82.8	80.3	83.4
2019	F3	F319	F319P3	68.9	80.8	86.7	94.2
2019	F3	F319	F319P3	58.6	82.8	80.3	94.2
2019	F3	F319	F319P3	58.6	82.8	80.3	94.2
2019	F3	F319	F319P4	86.9	91.7	75.2	80.6
2019	F3	F319	F319P4	86.9	91.7	75.2	80.6
2019	F3	F319	F319P4	86.9	91.7	75.2	80.6
2019	F3	F319	F319P5	80.6	90.3	90.7	94
2019	F3	F319	F319P5	80.6	90.3	90.7	94
2019	F3	F319	F319P5	80.6	90.3	90.7	94
2019	F4	F419	F419P1	59.3	61.6	100.5	96.4
2019	F4	F419	F419P1	59.3	61.6	100.5	96.4
2019	F4	F419	F419P1	59.3	61.6	100.5	96.4
2019	F4	F419	F419P2	34.3	72.6	60.8	83.5
2019	F4	F419	F419P2	34.3	72.6	60.8	83.5
2019	F4	F419	F419P2	34.3	72.6	60.8	83.5
2019	F4	F419	F419P3	93.3	81.5	96.7	85.2
2019	F4	F419	F419P3	93.3	81.5	96.7	85.2
2019	F4	F419	F419P3	93.3	81.5	96.7	85.2
2019	F4	F419	F419P4	52.1	66.7	100.1	79
2019	F4	F419	F419P4	52.1	66.7	100.1	79
2019	F4	F419	F419P4	52.1	66.7	100.1	79
2019	F4	F419	F419P5	61.3	82.9	94.4	83.2
2019	F4	F419	F419P5	61.3	82.9	94.4	83.2
2019	F4	F419	F419P5	61.3	82.9	94.4	83.2
2019	F5	F519	F519P1	64.1	68.9	96.9	98.8
2019	F5	F519	F519P1	64.1	68.9	96.9	98.8
2019	F5	F519	F519P1	64.1	68.9	96.9	98.8
2019	F5	F519	F519P2	75.8	71.8	72.6	94.2
2019	F5	F519	F519P2	75.8	71.8	72.6	94.2
2019	F5	F519	F519P2	75.8	71.8	72.6	94.2
2019	F5	F519	F519P3	79.9	42.6	99.2	77.8
2019	F5	F519	F519P3	79.9	42.6	99.2	77.8
2019	F5	F519	F519P3	79.9	42.6	99.2	77.8
2019	F5	F519	F519P4	73.9	66.4	93.5	98.8
2019	F5	F519	F519P4	73.9	66.4	93.5	98.8
2019	F5	F519	F519P4	73.9	66.4	93.5	98.8
2019	F5	F519	F519P5	110.5	88.1	97.6	59.6
2019	F5	F519	F519P5	110.5	88.1	97.6	59.6
2019	F5	F519	F519P5	110.5	88.1	97.6	59.6

Table A1.2. Percentage Available Moisture at IATC site for 2021 and 2022

Percentage Available Moisture at IATC Site for 2021 and 2022													
%AM 2021							%AM 2022						
Date	**Depth**	**P1**	**P2**	**P3**	**P4**	**P5**	**Date**	**Depth**	**P1**	**P2**	**P3**	**P4**	**P5**
06-Jul	0-15	58	24	102	53	56	15-Jul	0-15	17	48	42	24	29
	15-30	86	102	102	94	103	15-Jul	15-30	61	68	81	71	78
	30-45	101	97	101	100	102	15-Jul	30-45	90	92	99	97	95
	45-60	103	100	103	98	105	15-Jul	45-60	108	102	97	104	101
	60-75	103	100	97	98	106	15-Jul	60-75	108	102	100	102	101
	75-90	105	101	107	97	100	15-Jul	75-90	100	106	99	104	101
	90-105	104	102	115	104	98	15-Jul	90-105	107	113	98	104	100
	105-120						15-Jul	105-120					
	120-135						15-Jul	120-135					
12-Jul	0-15	48	16	98	59	41	22-Jul	0-15	75	88	71	58	64
	15-30	96	94	104	97	103	22-Jul	15-30	98	101	100	100	100
	30-45	111	100	104	105	104	22-Jul	30-45	101	101	100	100	100
	45-60	107	103	102	102	107	22-Jul	45-60	101	99	99	101	100
	60-75	103	102	102	102	108	22-Jul	60-75	100	99	100	100	100
	75-90	104	103	107	100	102	22-Jul	75-90	101	100	100	100	101
	90-105	106	103	114	107	101	22-Jul	90-105	101	101	101	101	100
	105-120						22-Jul	105-120					
	120-135						22-Jul	120-135					
19-Jul	0-15	53	21	102	70	46	29-Jul	0-15	44	44	37	31	30
	15-30	99	99	102	100	101	29-Jul	15-30	75	65	87	71	78
	30-45	102	100	101	101	100	29-Jul	30-45	90	82	96	89	94
	45-60	97	99	103	101	100	29-Jul	45-60	89	90	93	98	95
	60-75	101	98	101	102	104	29-Jul	60-75	97	92	97	100	99
	75-90	100	102	103	101	101	29-Jul	75-90	94	95	98	99	97
	90-105	103	102	110	104	101	29-Jul	90-105	99	98	99	101	98
	105-120						29-Jul	105-120					
	120-135						29-Jul	120-135					
26-Jul	0-15	32	12	84	54	18	10-Aug	0-15	62	68	77	55	56
	15-30	67	75	103	98	91	10-Aug	15-30	94	88	101	90	100
	30-45	96	99	98	103	95	10-Aug	30-45	82	87	91	83	95
	45-60	93	95	98	99	96	10-Aug	45-60	83	68	92	88	89
	60-75	95	94	94	99	101	10-Aug	60-75	94	82	100	92	89
	75-90	100	96	100	98	99	10-Aug	75-90	82	95	94	93	93
	90-105	103	100	107	104	96	10-Aug	90-105	96	91	99	99	98
	105-120						10-Aug	105-120					
	120-135						10-Aug	120-135					
03-Aug	0-15	31	9	89	58	19	18-Aug	0-15	59	47	68	53	52
	15-30	63	74	101	98	96	18-Aug	15-30	88	75	98	81	92

	30-45	95	98	100	100	103	18-Aug	30-45	81	73	90	79	89
	45-60	88	94	97	99	100	18-Aug	45-60	74	73	94	88	87
	60-75	94	90	97	99	101	18-Aug	60-75	87	79	98	89	88
	75-90	99	95	101	100	98	18-Aug	75-90	81	83	94	91	91
	90-105	100	99	108	102	100	18-Aug	90-105	88	84	96	98	91
	105-120						18-Aug	105-120					
	120-135						18-Aug	120-135					
09-Aug	0-15	50	26	128	90	65	07-Sep	0-15	67	49	45	39	102
	15-30	102	119	105	99	121	07-Sep	15-30	102	87	104	95	98
	30-45	100	101	101	102	108	07-Sep	30-45	83	91	102	99	105
	45-60	89	93	98	98	101	07-Sep	45-60	92	78	99	103	95
	60-75	92	88	97	97	102	07-Sep	60-75	100	82	101	96	95
	75-90	95	91	99	94	96	07-Sep	75-90	84	81	99	97	101
	90-105	97	92	106	100	99	07-Sep	90-105	85	87	101	99	94
	105-120						07-Sep	105-120					
	120-135						07-Sep	120-135					
16-Aug	0-15	31	11	102	70	26							
	15-30	66	78	100	100	101							
	30-45	91	94	96	100	106							
	45-60	86	85	98	98	101							
	60-75	90	82	95	97	98							
	75-90	91	84	100	94	99							
	90-105	94	91	103	100	100							
	105-120												
	120-135												
23-Aug	0-15	52	28	126	90	59							
	15-30	108	121	106	108	126							
	30-45	92	108	99	106	119							
	45-60	98	94	103	103	114							
	60-75	97	88	99	99	111							
	75-90	94	92	101	99	101							
	90-105	98	93	108	102	99							
	105-120												
	120-135												

APPENDIX 2: IRRIGATION SYSTEMS INFORMATION

Table A2. List of irrigation system information for farms F1-F5 for 2019-2022 including which systems employed VRI technology

		Location	VRI?	Other Information
2022	F1	Vauxhall		
	F2	Chin	No	
	F3	Vauxhall		
	F4	Bow Island		
2021	F1	Vauxhall		
	F2	Chin	NO (Irrigate IQ removed!)	Section machine, one quarter in potatoes
	F3	Vauxhall		
	F4	Bow Island		West half of circle is potatoes
	F5	Taber	Yes	
2020	F1	Vauxhall	No	
	F2	Chin	Trimble Irrigate IQ VRI, complex zones drawn, system malfunctioning	Section machine, one quarter in potatoes, windshield wipe applied
	F3	Vauxhall	No	
	F4	Bow Island	?	
	F5	Taber	No	
2019	F1	Vauxhall	No	Corner arm
	F2	Chin	Trimble Irrigate IQ VRI, multi-zones	Section machine, one quarter in potatoes, windshield wipe applied
	F3	Vauxhall	No	Reinke corner arm with Trimble Irrigate-IQ Uniform Corner
	F4	Bow Island	Trimble Irrigate IQ VRI (only used on low areas)	West half of circle is potatoes - windshield wipe applied
	F5	Taber	Trimble Irrigate IQ VRI (separation in West, East only)	Corner arm with Trimble Irrigate-IQ Uniform Corner

Appendix 3: Additional Data Analysis

Physiological Degree Days

Physiological degree days (P-Days) were considered as an alternative to Growing Degree Days. P-days are often used in disease forecasting for potatoes and are another tool to predict the development of potato crops. Results from the analysis are provided in Table A3.1 below. Using P-days rather than GDD produced very similar results in that there was a lack of significant effect (p>0.10) on yield, though P-days appeared to have an insignificant positive relationship where GDD's had an insignificant negative relationship.

Table A3.1. Summary of statistical analysis results for different models investigating the relationship between various factors and potato yield. The table indicates the p-values indicating significance levels for each factor and the corresponding slopes.

			Tuber Initiation		Tuber Bulking	
		Depth	**0-35 cm**	**35-60 cm**	**0-35 cm**	**35-60 cm**
Total Yield	AM	p-value	0.45906	0.09192	0.08292	0.038596 *
		Slope	-0.02993	0.09686	0.1	-0.1145
	Topography	p-value	0.00214 **	0.00114 **	0.00151 **	0.000778 ***
		Slope	-3.25282	-3.4553	-3.35295	-3.58023
	P-Days	p-value	0.13251	0.12127	0.1304	0.103401
		Slope	0.20605	0.21222	0.20653	0.22265
	Soil Complexity	p-value	0.33202	0.42773	0.26611	0.244263
		Slope	-4.12522	-3.37474	-4.74282	-4.95179
Marketable Yield	AM	p-value	0.9868	0.1604	0.0424 *	0.00955 **
		Slope	-0.00068	0.08236	0.11909	-0.14602
	Topography	p-value	0.0656	0.0469 *	0.0511	0.02672 *
		Slope	-1.981	-2.14355	-2.0855	-2.38431
	P-Days	p-value	0.1313	0.1266	0.1414	0.10119
		Slope	0.2004	0.20259	0.19581	0.21645
	Soil Complexity	p-value	0.4499	0.5466	0.3726	0.32069
		Slope	-3.157	-2.52286	-3.75219	-4.13163

Note:

*: p-value < 0.1 (marginally significant)

**: p-value < 0.05 (significant)

***: p-value < 0.01 (highly significant)

Potato Quality

Several parameters of quality were also investigated in this study. The main quality parameter we were concerned about was Specific gravity, but analysis was also conducted for % glucose and sucrose as well. Specific gravity was mainly influenced by weather conditions. In 2019, there was no analysis done on % glucose or % sucrose rating. Overall, there were no significant relationships (p>0.10) between topography, soil variables and the % glucose and sucrose (Table A3.2).

Table A3.2. Summary of statistical analysis results for different models investigating the relationship between various factors and quality. The table indicates the p-values indicating significance levels for each factor and the corresponding slopes.

			Tuber Initiation		**Tuber Bulking**	
		Depth	**0-35 cm**	**35-60 cm**	**0-35 cm**	**35-60 cm**
Specific Gravity	AM	p-value	0.52067	0.645831	0.519052	0.746136
		Slope	-2.40E-05	2.36E-05	3.43E-05	1.66E-05
	Topography	p-value	0.26063	0.280003	0.320853	0.259976
		Slope	1.10E-03	1.06E-03	9.77E-04	1.11E-03
	GDD	p-value	0.00133 **	0.000781 ***	0.000739 ***	0.000861 ***
		Slope	-4.38E-05	-4.58E-05	-4.60E-05	-4.53E-05
	Soil Complexity	p-value	0.5339	0.548541	0.466531	0.498893
		Slope	1.38E-03	1.33E-03	1.61E-03	1.50E-03
% Glucose	AM	p-value	0.606	0.516	0.3339	0.0638.
		Slope	0.0000388	-0.00006579	-0.0001026	-0.000174
	Topography	p-value	0.9	0.954	0.7966	0.899
		Slope	0.0002259	0.0001046	0.0004688	-0.000229
	GDD	p-value	0.16	0.206	0.1951	0.169
		Slope	-0.00004627	-0.00004167	-0.00004264	-0.00004439
	Soil Complexity	p-value	0.256	0.211	0.3045	0.2994
		Slope	0.006069	0.006797	0.005556	0.005472
Sucrose Rating	AM	p-value	0.347	0.534	0.00863 **	0.0278 *
		Slope	-0.003968	0.003573	-0.015396	-0.011519
	Topography	p-value	0.622	0.558	0.36509	0.7977
		Slope	0.049269	0.058816	0.090357	0.025583
	GDD	p-value	0.363	0.45	0.32937	0.4002
		Slope	0.002213	0.00188	0.002335	0.002055
	Soil Complexity	p-value	0.696	0.808	0.955	0.897
		Slope	0.142595	0.090968	-0.020395	0.047389

Note:

*: p-value < 0.1 (marginally significant)

**: p-value < 0.05 (significant)

***: p-value < 0.01 (highly significant)

Disease

Disease occurrence was also investigated in part of the final analysis, but not included in the main report. Some significant effects were noted, with the greatest and most consistent relationship with GDD, where greater GDD, likely reflective of hotter and drier weather, was associated with lower disease occurrence.

Table A3.3. Summary of statistical analysis results for different models investigating the relationship between various factors and disease. The table indicates the p-values indicating significance levels for each factor and the corresponding slopes.

			Tuber Initiation		Tuber Bulking	
		Depth	**0-35 cm**	**35-60 cm**	**0-35 cm**	**35-60 cm**
Hollow Heart	AM	p-value	0.43836	0.88808	0.6964	0.09383 .
		Slope	0.004358	-0.001119	-0.003064	-0.0129
	Topography	p-value	0.01666 *	0.02001 *	0.0185 *	0.00947 **
		Slope	-0.35225	-0.345312	-0.346749	-0.38502
	GDD	p-value	0.01164 *	0.01405 *	0.0143 *	0.01159 *
		Slope	-0.00602	-0.005706	-0.005667	-0.005787
	Soil Complexity	p-value	0.20586	0.19312	0.2078	0.1464
		Slope	-0.519815	-0.533644	-0.512375	-0.587237
Vascular Discoloration	AM	p-value	0.842973	0.19932	0.164052	0.577857
		Slope	0.002899	0.02737	-0.027535	0.011362
	Topography	p-value	0.14929	0.104916	0.152278	0.187252
		Slope	-0.564346	-0.63809	-0.557746	-0.521882
	GDD	p-value	0.000503 ***	0.000282 ***	0.000874 ***	0.000515 ***
		Slope	-0.014774	-0.01507	-0.014065	-0.014545
	Soil Complexity	p-value	0.617693	0.491742	0.518086	0.588952
		Slope	0.339399	0.4625	0.452895	0.369882
Brown Centre	AM	p-value	0.532	0.022934 *	0.839	0.038596 *
		Slope	0.006573	0.033446	0.003007	-0.1145
	Topography	p-value	0.119	0.067609 .	0.123	0.000778 ***
		Slope	-0.42568	-0.499406	-0.422382	-3.58023
	GDD	p-value	7.72e-05 ***	8.21e-05 ***	7.71e-05 ***	0.103401
		Slope	-0.023953	-0.024016	-0.023565	0.22265
	Soil Complexity	p-value	0.165	0.26267	0.154	0.244263
		Slope	-1.209145	-0.980899	-1.235722	-4.95179

Note:

*: p-value < 0.1 (marginally significant)

**: p-value < 0.05 (significant)

***: p-value < 0.01 (highly significant)