

**Remote and Proximal Sensing for Potato Nitrogen Status Assessment and
Yield Prediction in Manitoba, Canada**

by

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Abstract

Potato production requires accurate and timely assessment of crop nitrogen (N) status and yield potential, yet conventional field sampling is labour-intensive, spatially limited, and often inadequate for representing within-field variability. This dissertation examined the use of remote and proximal sensing, integrated with machine learning (ML) and deep learning (DL), for potato N assessment and yield prediction under Manitoba field conditions. It combined critical synthesis of the Canadian evidence base with empirical evaluation of sensing approaches of increasing spectral and structural complexity to clarify how different forms of sensor-derived information contribute to prediction under field conditions. The review component showed that remote and proximal sensing have clear value for potato nutrient and yield management in Canada, but that the available literature remains geographically concentrated and methodologically inconsistent. Empirical analyses then demonstrated that unmanned aerial vehicle (UAV)-derived multispectral imagery can support in-season estimation of petiole nitrate-N (NO_3^- -N), with the best Random Forest model reaching $R^2 = 0.571$ and $\text{RMSE} = 0.459\%$ after recursive feature elimination, indicating that prediction depended on both algorithm selection and feature composition. The analysis was extended through visible and near-infrared to shortwave infrared (VNIR-SWIR) hyperspectral reflectance spectroscopy acquired under field and laboratory conditions. In Chapter 4, the strongest petiole NO_3^- -N prediction was obtained from laboratory fresh-leaf spectra using a one-dimensional convolutional neural network (1D-CNN; $R^2 = 0.90$, $\text{RMSE} = 0.22\%$), compared with $R^2 = 0.77$ and $\text{RMSE} = 0.27\%$ for the best field canopy model. Calibration transfer improved field-based prediction, increasing 1D-CNN performance to $R^2 = 0.82$. The dissertation further evaluated UAV-derived light detection and ranging (LiDAR) and multispectral data within single-task and multi-task DL frameworks for simultaneous estimation of tuber yield and petiole NO_3^- -

N. Multi-task learning improved yield prediction more consistently than petiole NO_3^- -N prediction, increasing test-set yield R^2 from 0.26 under the best single-task model to 0.46–0.60 under multi-task models. Yield prediction relied more broadly on spectral and LiDAR-derived structural features, whereas petiole NO_3^- -N prediction was mainly driven by spectral indicators. Overall, the findings clarify how sensing depth, data type, and modelling framework shaped potato N status assessment and yield prediction under the conditions investigated.

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Contributions of Authors

This dissertation is presented in manuscript-based format in accordance with the regulations of the Faculty of Graduate and Postdoctoral Studies at the University of Manitoba. Ehsan Chatraei Azizabadi is the first author and primary contributor to all manuscripts included in the dissertation. He held principal responsibility for developing the research questions, conducting the research, analyzing and interpreting the results, and preparing the manuscripts. The specific contributions of the candidate and co-authors are described below.

For Chapter 2, Ehsan Chatraei Azizabadi led the entire review process, including its conceptualization, literature search, synthesis and interpretation of the literature, preparation of the tables and figures, and writing of the manuscript. Nasem Badreldin provided supervision, contributed to the conceptual development of the review, and critically reviewed and revised the manuscript.

For Chapter 3, Ehsan Chatraei Azizabadi led the design and execution of the study, coordinated data acquisition, performed the principal data processing and analysis, interpreted the findings, prepared the visual materials, and led the writing of the manuscript. Nasem Badreldin contributed to the conceptualization and methodology, provided supervision and project administration, secured funding, and reviewed and revised the manuscript. Mohamed El-Shetehy contributed to the methodology, formal analysis, provision of resources, validation, and review of the manuscript. Xiaodong Cheng and Ali Youssef contributed to validation, interpretation, visualization, and critical review of the manuscript.

For Chapter 4, Ehsan Chatraei Azizabadi led the conceptualization and execution of the study, spectral data acquisition and curation, software implementation, model development, formal

analysis, validation, interpretation, visualization, and preparation of the original manuscript. Masoomeh Gomroki contributed to the methodology, data curation, software implementation, analysis, visualization, and review and revision of the manuscript. Mohamed El-Shetehy contributed to the methodology, investigation, provision of resources, project administration, and review and revision. Keshav D. Singh contributed to the methodology, validation, and critical review of the manuscript. Abdul-Wahab Mossa contributed to the methodology, formal analysis, validation, and critical review. Nasem Badreldin provided supervision, project administration, and resources, contributed to the conceptualization and methodology, secured funding, and reviewed and revised the manuscript.

For Chapter 5, Ehsan Chatraei Azizabadi led the conceptualization and execution of the study, data acquisition and curation, software development, formal analysis, validation, interpretation, visualization, and preparation of the original manuscript. Nasem Badreldin provided supervision and project administration, contributed to the conceptualization, methodology, and validation, secured funding, and reviewed and revised the manuscript.

Chapters 1 and 6 were conceived and written solely by Ehsan Chatraei Azizabadi. All co-authors reviewed and approved the manuscripts on which they appear.

Copyright and Publication Information

Chapters 2–5 of this dissertation are based on published journal articles. The publication details and copyright status of these works are provided below.

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Artificial Intelligence Use Statement

Artificial intelligence tools were used only for limited editorial support, including language refinement, grammar correction, and improvement of sentence clarity. No artificial intelligence tools were used in the conception of the research, formulation of the objectives, methodological design, data collection, data analysis, interpretation of findings, or development of the scholarly content of this dissertation. The author takes full responsibility for the content, interpretation, and conclusions presented in this work.

Chapter 1

General Introduction

1.1. Research context

Agriculture faces the continuing challenge of increasing food production while reducing pressure on land, water, and environmental resources, making more efficient crop monitoring and management a major research priority (Foley et al., 2011; Godfray et al., 2010; Tilman et al., 2011). In crop production systems, this challenge is closely tied to the need for timely and reliable information on crop condition throughout the growing season, particularly where field performance is shaped by the interacting effects of soil properties, weather conditions, and management practices (Thenkabail, 2024; Wu et al., 2023).

Among the agronomic factors that govern crop productivity, nutrient availability remains one of the most important because plant growth and yield formation depend on an adequate supply of essential nutrients (Agegnehu et al., 2016; C. He et al., 2025). Nitrogen (N) is especially critical in this regard, yet its availability varies over time and across space in response to soil processes, weather variability, and management decisions, making accurate assessment under field conditions inherently difficult (Gonzalez-Maldonado et al., 2025; Z. Li, Guan, et al., 2022; Singh et al., 2025). This difficulty is further intensified by the fact that conventional ground-based assessment methods are labour-intensive and often inadequate for capturing the dynamic variability of crop and environmental conditions (F. Zhang et al., 2025).

Remote sensing (RS) has become an increasingly important tool in agricultural monitoring because it enables repeated observations and spatially explicit characterization of crop conditions across heterogeneous production environments (Lobell, 2013). Compared with site-specific field measurements, remotely sensed data can capture within-field and landscape-scale variability more effectively and thereby improve the identification of spatial production constraints (Radočaj et al.,

2026). These capabilities have reinforced the role of RS in agricultural research by enabling repeated, large-area observation of crop conditions, supporting multi-scale analysis, and providing information that can be used across a wide range of applications, including crop monitoring, yield estimation, and plant stress detection (Karmakar et al., 2024). Complementing these broader-scale observations, proximal sensing provides close-range, non-destructive optical measurements that can improve field-level diagnosis of crop N status and support more precise characterization of within-field variability. Such measurements are particularly valuable for repeated in-season assessment, but their interpretation depends on phenological stage, seasonal conditions, and appropriate calibration linking sensor response to plant N status (Argento et al., 2025; Gabriel et al., 2017; Padilla et al., 2016).

The growing availability of remotely sensed data has also increased the importance of predictive modelling in agricultural research. Such approaches are especially relevant because crop responses emerge from complex and often non-linear interactions among environmental conditions, soil characteristics, and management factors (Y. Wang et al., 2024). Within this broader context, potato provides a particularly compelling case for evaluating sensing-based and data-driven methods, as it is among Canada's major field crops by production volume while also presenting pronounced N-management challenges under intensive production, especially where residual nitrate and seasonal drainage increase the potential for off-site losses (FAOSTAT, 2026a; Y. Jiang et al., 2022).

1.2. Dissertation rationale

Reliable estimation of crop yield and N status remains important because both have direct implications for harvest forecasting, fertilizer management, and within-field decision-making (Iniyan et al., 2023; D. M. Johnson, 2014; Shingade & Mudhalwadkar, 2024). The significance of

N assessment is further heightened by its environmental consequences, particularly in production systems where inefficient fertilizer use contributes to greenhouse gas emissions and N losses through nitrate leaching, runoff, ammonia volatilization, and denitrification (Environment and Climate Change Canada, 2025; H. Tian et al., 2020). In Canada, this issue is especially consequential because agricultural soils constitute a major national source of nitrous oxide emissions, while fertilizer-derived N inputs remain closely associated with both emission intensity and the risk of nutrient loss (De Laporte et al., 2021; FAOSTAT, 2026b).

At the same time, the central methodological challenge lies not only in data availability, but in developing predictive frameworks that remain reliable when applied beyond the temporal or spatiotemporal extent of model development (Filippelli et al., 2024). This challenge is fundamentally one of prediction rather than explanation, since useful models must be judged by their out-of-sample performance rather than by explanatory fit alone, with particular importance therefore attached to model structure, validation design, and the quality of the input data (Shmueli, 2010). In agricultural systems, predictive approaches now span process-based crop simulation, statistical learning, and model-data fusion, reflecting both the biological complexity of crop responses and the need for modelling frameworks capable of accommodating that complexity (Breiman, 2001; Huang et al., 2019; Jin et al., 2018; Jones et al., 2003).

Against this background, the rationale for this dissertation was to address a gap between the expanding use of sensing technologies and the limited clarity on how different sensing modalities and modelling approaches contribute to potato N assessment and yield prediction. Existing work has often examined individual sensing sources or modelling strategies separately, making it difficult to determine their relative and combined value within a broader predictive context. This dissertation was therefore undertaken to provide a more integrated evaluation of sensing-based

approaches for potato systems and to clarify their relevance both for assessing potato crop performance and for strengthening predictive research on sensing-based crop assessment.

1.3. Overall aim and specific objectives

The overall aim of this dissertation was to develop and evaluate sensing-based and data-driven approaches for potato N status assessment and yield prediction under field conditions in Manitoba, Canada. The dissertation was structured to move from synthesis of the Canadian research landscape to empirical evaluation of sensing and modelling approaches with increasing spectral, structural, and analytical complexity.

The specific objectives of this dissertation were to:

1. critically review the Canadian literature on potato yield and N management using RS, proximal sensing, and machine learning (ML), with attention to the scope of the existing evidence base and the principal research gaps that remain;
2. investigate the relationships between unmanned aerial vehicle (UAV)-derived multispectral variables and potato petiole NO_3^- -N concentration, and evaluate the performance of supervised ML models and feature selection methods for in-season N prediction under field conditions;
3. assess the potential of visible and near-infrared to shortwave infrared (VNIR-SWIR) hyperspectral reflectance spectroscopy for potato N status prediction across field and laboratory conditions, and compare deep learning (DL), ML, and regression-based approaches for this purpose;

4. determine the predictive value of integrated UAV-derived multispectral and light detection and ranging (LiDAR) data for in-season estimation of end-of-season potato yield from row-closure observations and petiole NO_3^- -N status, and evaluate whether multi-task deep learning offers advantages over single-task modelling for these two response variables;
5. synthesize the dissertation findings to clarify the contributions of multispectral, hyperspectral, and LiDAR-based approaches to potato N status assessment and yield prediction, and to identify implications for future sensing-based nutrient management research in potato systems.

1.4. Scope of the dissertation

This dissertation examines potato N status and yield assessment under Manitoba field conditions using selected sensing and modelling approaches. It is centred on three sources of information: UAV-derived multispectral imagery, VNIR-SWIR hyperspectral spectroscopy, and UAV-derived LiDAR data.

The analysis is restricted to the response variables addressed in the manuscript chapters, with particular focus on petiole-based NO_3^- -N measures and tuber yield. It is also confined to the analytical strategies implemented in those chapters, including ML and DL models developed from sensor-derived variables. In the empirical chapters, the reference variables and predictor variables do not always occupy the same observational scale. In particular, petiole NO_3^- -N is a tissue-specific chemical measurement, whereas several predictor sets were derived from canopy-scale optical or structural observations; the resulting models should therefore be interpreted as estimating physiologically related crop status from indirect sensing signals rather than as direct measurement of the sampled tissue itself.

The dissertation is not intended to provide an exhaustive treatment of all sensing platforms, crop traits, or modelling frameworks relevant to precision agriculture. Nor does it extend to fertilizer recommendation systems, economic optimisation, or full farm-scale implementation. Its purpose is to evaluate the role of selected sensing approaches in potato N and yield assessment and to define their relevance within the conditions investigated.

1.5. Organisation of the dissertation and linkage among chapters

This dissertation follows a manuscript-based format and is composed of six chapters. Chapter 1 introduces the research context, sets out the rationale for the dissertation, states the overall aim and specific objectives, defines the scope of the work, and explains the structure of the dissertation. Chapter 2 reviews the Canadian literature on potato yield and N management using RS, proximal sensing, and ML. It establishes the broader scholarly context for the dissertation and identifies the principal themes and research gaps that shaped the empirical work that follows.

Chapter 3 examines in-season potato N prediction using UAV-derived multispectral data and ML. It marks the transition from literature synthesis to field-based analysis and evaluates the capacity of multispectral information to represent N status under experimental conditions. Chapter 4 extends this line of inquiry by evaluating VNIR-SWIR hyperspectral reflectance spectroscopy for potato N assessment. Unlike Chapter 3, which relies on UAV multispectral imagery, this chapter considers hyperspectral measurements collected under both field and laboratory conditions, thereby broadening the spectral dimension of the dissertation. Chapter 5 advances the dissertation further by integrating UAV-derived LiDAR and multispectral data within a multi-task DL framework for in-season estimation of end-of-season potato yield from row-closure observations and potato N status. In doing so, it moves beyond single-response N assessment toward combined

analysis of structural and spectral information for the estimation of two agronomically important outcomes. Chapter 6 presents the overall synthesis of the dissertation. It brings together the main findings of the preceding chapters, clarifies their collective contribution to sensing-based potato research, and outlines the principal conclusions and directions for future work. Because this dissertation is manuscript-based, minor differences in terminology are retained across chapters. Specifically, Chapter 3 uses petiole NO_3^- -N concentration (PNC), whereas Chapters 4 and 5 use petiole nitrate-N (PNN); these abbreviations are retained from the original manuscripts and refer to petiole-based NO_3^- -N measures reported in those chapters.

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Chapter 2

**A Review on Potato Crop Yield and Nitrogen
Management Utilizing Remote/Proximal Sensing
Technologies and Machine Learning Models
in Canada**

2.1. Abstract

Potatoes are a vital part of our diet worldwide, but their cultivation poses challenges due to environmental impacts from traditional farming methods. Precision agriculture offers a promising solution by managing variability in crop growth and reducing environmental disturbance. Remote sensing technologies have become crucial for monitoring crops and field dynamics more efficiently. In potato farming, remote and proximal sensing technologies can support the prediction of yield and plant nutrient status. This capability allows farmers to identify spatiotemporal variation in yield and nutrient status and to make more precise site-specific management decisions. It is also valuable for monitoring plant nitrogen status during the growing season, thereby supporting timely fertilizer application to optimize yield while reducing environmental impacts. While still evolving, remote sensing transforms potato farming by providing detailed, non-invasive insights that can enhance productivity and sustainability. Research into different technologies and machine learning models for potato farming in Canada has been largely confined to a few provinces. This review aimed to identify this knowledge gap, underscoring the need for broader exploration of innovative agricultural methods across diverse regions of the country.

2.2. Introduction

The necessity of improving agricultural techniques has become critically important in tackling the food shortage crisis in several ecosystems of the world, mostly due to recurrent droughts and evident degradation of soil health, especially for a strategic crop like the potato (*Solanum tuberosum* L.), which plays a vital role due to its environmental adaptability and cost affordability (Raigond et al., 2020a). Potatoes are one of four crops that fulfill 50% of the world's food and energy demands, along with rice, wheat, and maize (Durst & Bayasgalanbat, 2014). Potatoes are

rich in carbohydrates, especially starch, and provide essential vitamins (C and B6), minerals (potassium, magnesium, phosphorus, and iron), high-quality protein and dietary fibre (Górska-Warsewicz et al., 2021). According to Agriculture and Agri-Food Canada (AAFC), Canadian potatoes are internationally renowned and exported for their exceptional safety and quality standards, with the Russet Burbank variety being the most widely produced. In Canada, potato production reached more than 6 million tons in 2022 (0.8% rise year-over-year), with the highest portion of this amount produced in Alberta (AB) (21.8%), followed by Prince Edward Island (PEI) (21.6%) and Manitoba (MB) (21.3%) (Statistics Canada, 2022). Potato crops typically require substantial nitrogen (N) fertilizer applications to achieve the desired tuber yield and size standards set by the industry (Y. Jiang et al., 2012), yet in Canada, the efficiency of this fertilizer often remains below 50-60%, similar to global trends (Ross et al., 2008). Therefore, implementing advanced digital agricultural technologies to monitor potato growth is essential for assessing crop nutrient status and providing useful field management advice (H. Liu et al., 2020a; N. Liu et al., 2020).

Potatoes require sufficient N fertilizer, typically recommended at a rate of 125-200 kg ha⁻¹ in regions such as Manitoba, to achieve optimal yield and quality, particularly on coarse-textured soils prone to N loss, necessitating efficient fertilizer management to sustain productivity (X. Gao et al., 2018). The ideal fertilizer application rate for maximum yield depends on location, growing conditions, crop management, soil N status, crop N demand, soil properties, and target yield (Ünal & Kızıldeniz, 2023). Conventional farming practices, by often overlooking field variability in topography, soil composition, and crop conditions, can contribute to issues such as nutrient leaching, environmental contamination, and reduced profitability due to misaligned input applications (Neupane & Guo, 2019). Furthermore, improving the efficient utilization of fertilizer

N could enhance consumer trust in the sustainability of crop production and food security, consequently facilitating expanded market opportunities for producers (Urso & Gilbertson, 2018). Potato crop production in Canada is facing great challenges, such as the recent substantial rise in N fertilizer costs which has led to initiatives aimed at developing strategies to enhance N-use-efficiency (NUE) in important crops like potatoes (Cohen et al., 2010). Three prairie provinces, AB, Saskatchewan (SK), and MB, account for about 75% of total N fertilizer applications in Canada (Mezbahuddin et al., 2020). With reported low NUE in AB (30-50%), the risk of losses through volatilization, leaching, and denitrification processes is high, necessitating a reduction in N losses from agro-ecosystems to mitigate the environmental impact of crop production in western Canada (Mezbahuddin et al., 2020). Various factors have been identified as influencing crop growth and NUE, such as crop rotation, genotype, tillage practices, timing and placement of N application, and water availability (Dutta et al., 2017).

In response to the increasing number of people and urban expansion reducing arable land, modern agriculture seeks to minimize water, fertilizer, and pesticide use while meeting rising production demands, with precision agriculture (PA) offering site-specific management (SSM) solutions using spatiotemporal data (such as satellite imagery, drones, GPS technology, and sensors) and analysis to optimise yield-limiting factors (Griffel et al., 2018). Monitoring potato N status is most effectively done through the petiole sap NO_3^- -N test, which is widely regarded as the top indicator for this purpose (Hunt Jr et al., 2018). Petioles are one tissue where N is transported and stored in the form of nitrate (Rosen & Bierman, 2008). However, there are several challenges to using petiole NO_3^- -N for monitoring crop N status, including its time-consuming and labour-intensive measurement process, high variability among plants and over time due to varying growth conditions and soil conditions, and the risk of promoting vine growth rather than tuber growth with

responsive N applications (N. Liu et al., 2021). Above-ground biomass (AGB) serves as an important indicator of crop growth status and is closely linked to crop nutrition and yield, highlighting its value for implementing targeted crop management practices based on spatio-temporal dynamics (B. Li et al., 2020a). Additionally, spatially variable fertilizer application addresses multiple factors affecting crop productivity, balancing economics and environmental concerns (H. Khan et al., 2020). Scientists have developed spaceborne, airborne, and ground-based platforms with various sensors, providing rapid, non-destructive data collection over large regions, making remote sensing (RS) a promising tool for PA (Alkhaled et al., 2023).

Recent studies have linked spectral indices to plant N content based on canopy reflectance, but accurately estimating N content faces challenges due to canopy structure variations during vegetative growth (H. Yang et al., 2023). Furthermore, machine learning (ML), along with big data and high-performance computing, revolutionizes PA, optimising productivity and resource use through tasks like yield mapping, estimation, supply-demand matching, and crop quality prediction (Alkhaled et al., 2023). This study provides an overview of the potato plant spectrum under N deficiency and reviews sensing-based approaches for potato yield and N management in Canada. The study highlights advancements in precision agriculture, including RS and ML, to enhance productivity and sustainability.

2.3. Remote and proximal sensing in crop monitoring

Proximal sensing (PS) refers to the collection or sensing of data obtained in close proximity to crops (Araus & Cairns, 2014). Proximal sensors have several benefits, including high-resolution imagery, independence from external conditions like cloud cover, suitability for small fields, and straightforward application, such as mounting on a tractor (Anastasiou et al., 2018). With proper

processing, the abundant and precise data obtained from PS can generate highly reliable and valuable predictive maps (Di Gennaro et al., 2017; Fountas et al., 2014). Proximal sensing can utilise both portable and fixed spectrometers to capture spectra at leaf and canopy levels in both laboratory and outdoor settings (Sanaeifar et al., 2023). Information related to pigment constituents, including chlorophyll (Cogliati et al., 2015), carotenoids (Gitelson et al., 2006), and anthocyanins (Baluja et al., 2012), is frequently derived from spectrometer and infrared-imager data (Yoosefzadeh-Najafabadi et al., 2023). These devices are also utilised to detect non-pigment constituents such as N (Omid et al., 2020), protein (Goswami et al., 2023), lignin, and cellulose (Kokaly et al., 2009). In contrast to PS, which is primarily used for high-resolution data collection on a small scale, RS provides systematic information over large areas (Darra et al., 2021). Modern RS relies heavily on UAVs, airborne platforms, and spaceborne sensors, which employ both passive and active methods to capture electromagnetic reflectance across a broad spectrum of frequencies (Gholizadeh & Kopačková, 2019). Khanal et al. (2020) offered an in-depth review of the advancements and capabilities of newly developed satellite sensors, detailing their technological progress and applications.

2.4. Machine learning for predicting tuber yield and nitrogen status in potato crops

Recently, the integration of ML techniques with remotely sensed data has emerged as a widely adopted method for estimating vegetation parameters (Han et al., 2019; J. Wang et al., 2018). ML facilitates enhanced decision-making and informed real-world actions through its capability to integrate expert knowledge seamlessly, offering a robust framework for data-driven decision-making processes (Chlingaryan et al., 2018). ML predicts and enhances crop productivity by developing models that analyse factors influencing crop responses, with various models used for

predictions (Pant et al., 2021). ML algorithms offer several key advantages: they excel at modelling non-linear relationships between multiple data sources, their performance is typically enhanced with more training data, and they can handle noisy data effectively through regularization techniques that reduce variance and generalization error (Paudel et al., 2021). Recent research indicates that the integration of ML algorithms has demonstrated notable advancements in enhancing the predictive accuracy and resilience of crop nutrient prediction models (Fu et al., 2021).

Efficient and precise pre-harvest crop yield predictions are essential for effective food market operations and optimising agricultural production for maximum output with minimal resource input, aiding in the early detection of yield-affecting factors to minimize losses and ensure planned profitability (Piekutowska et al., 2021). Predicting crop productivity before harvest is vital for stakeholders to optimise production and for governments to enhance food security (Weiss et al., 2020). Yield prediction necessitates diverse expertise in agronomy, meteorology, statistics, economics, and computer science, with recent research focusing on rice and maize; however, potato's belowground edible part presents distinctive challenges in this field (Lin et al., 2023). Potato production can be limited by climate-related factors such as cool temperatures delaying shoot emergence, uneven rainfall causing flood or drought stress, and prolonged humidity and cool weather intensifying foliar diseases like late blight (He et al., 2012). Other yield-limiting factors include nutrient needs, uptake patterns, availability factors, assessment methods, and fertilizer and water management practices (Stark et al., 2020). Methods for predicting potato traits like leaf area index (LAI), biomass, yield, or biochemical factors such as leaf N, water, and chlorophyll content, revolve around creating models that correlate spectral signals from RS data with field measurements (Alkhaled et al., 2023).

Another essential concern for crop growers is the early verification of plant N status, enabling timely remediation of N deficiency and informed in-season field management strategies (Fu et al., 2021). For accurate N management, establishing a strong correlation between RS data and crop N status often relies on parametric regression models, which can be linear or non-linear in nature (J. Peng et al., 2021a). Thus, predicting crop yield and estimating N status are intricately connected, essential for making informed fertilizer management decisions that span both pre-season planning and in-season adjustments (Chlingaryan et al., 2018).

In recent times, there has been a shift away from conventional potato yield prediction models like SUBSTOR, POTATO, and LINTUL-POTATO, reflecting dissatisfaction with classical regression models due to their significant forecast errors, which are deemed unsuitable for practical agricultural applications (Kurek et al., 2023). There are two primary categories of predictive models: statistical models, which rely on mathematical equations to describe variable relationships, and ML models, which utilise algorithms to learn from data (Ahmad & Sharma, 2023). According to Klompenburg et al. (2020), Neural Networks (NN) and Linear Regression are the most commonly used algorithms, with Random Forest (RF) and Support Vector Machines (SVM) also widely employed in various studies.

Artificial Neural Networks (ANNs) are highly valuable for predicting crop yields and classifying agricultural data due to their capacity to learn intricate non-linear relationships from diverse datasets like plant characteristics (Pandey & Mishra, 2017). ANNs are widely used for nonlinear regression tasks, characterized by their architecture comprising one input layer, multiple hidden layers, and one output layer. However, they are prone to overfitting, relying heavily on input quality and facing difficulties when handling unfamiliar data points outside their trained range (K. Berger et al., 2020). The study by Piekutowska et al. (2021) developed and validated both linear

(multiple linear regression (MLR)) and non-linear (ANN) models for forecasting tuber yield in three early potato cultivars, with the neural network model demonstrating superior prediction accuracy and quality compared with the multiple linear regression (MLR) model. Goffart et al. (2022) highlighted that integrating Sentinel-2 satellite data with biophysical and meteorological inputs supports robust MLR models, favouring N uptake and biomass for optimising potato N fertilization.

Support Vector Regression (SVR) (Smola & Schölkopf, 2004a) has emerged as a widely used ML technique in image processing applications owing to its versatility and capacity to manage datasets exhibiting multicollinearity (Verrelst et al., 2012). SVM relies on kernel functions to map complex, nonlinear problems into higher-dimensional spaces, thereby transforming them into linear problems, guided by the principles of structural risk minimization and statistical theory (Y. Shi et al., 2020). Several studies have explored SVM applications in various aspects of potato farming, including yield estimation (Kurek et al., 2023), quality assessment (Su & Xue, 2021), and analysis of tuber shape and size (Shen et al., 2022).

The Random Forest Regression (RFR) (Segal, 2003) is also a widely used approach for classification and regression tasks in ML and is known for its computational efficiency and robustness against overfitting. RFR utilises an ensemble approach by aggregating numerous regression trees, each constructed with hierarchical conditions applied sequentially from the root to the tree's leaves (X. Zhou et al., 2016). Numerous studies have investigated RFR applications for various crops, including potatoes. For example, Jeong et al. (2016) examined the effectiveness of RFR in predicting crop yields across global and regional scales in wheat, maize, and potato, demonstrating superior performance compared to MLR across various datasets and regions. Another study by Li et al. (2020) demonstrated the effectiveness of unmanned aerial vehicle

(UAV)-based RGB and hyperspectral imaging combined with RFR models for accurately estimating potato AGB ($R^2 > 0.90$) and predicting crop yield ($R^2 = 0.63$ for narrow-band vegetation indices (VIs) and crop height, $R^2 = 0.81$ using full wavelength spectra), underscoring their significance in site-specific crop management. In another study, Tang et al. (2024) developed a remote sensing algorithm with hyperspectral data (350–1830 nm) for predicting potato N content, with the RF model showing superior performance ($R^2=0.869$) compared to SVM and neural network models.

In addressing challenges like overfitting, generic AI techniques often require rigorous optimisation methods within deep network architectures to mitigate issues such as local minima, where the backpropagation algorithm enhances accuracy by optimising both backward and forward processes. Applying these advancements, in a study on potato yield prediction, the Deep neural networks (DNN) model outperformed other artificial intelligence techniques such as SVM and ANN, achieving an RMSE of 0.95 t ha^{-1} and an R^2 of 0.97 (Singha & Swain, 2022).

2.5. Features for predicting yield and nitrogen status of potato using ML models

Uniform conventional farming methods can constrain crop yields, compromise product quality, degrade the environment, and decrease farm income due to overuse and loss of agrochemicals (Farooque et al., 2020). Predicting agricultural outcomes, such as crop yield, is a complex process influenced by numerous factors spanning the entire growth cycle of the plants (Piekutowska et al., 2021). Constructing accurate production models relies on a thorough understanding of the research subject, encompassing knowledge of yield determinants and potential disturbances, which enables independent modification of modelling outcomes and enhances the effectiveness of the final model (Noman et al., 2023; Piekutowska et al., 2021). Testing models with different feature sets is crucial

for improving performance, as dimensionality reduction simplifies models, speeds up training, enhances interpretability, maximizes accuracy by selecting an optimal subset of features, and helps prevent overfitting, especially in datasets with many attributes (Pham et al., 2022).

Crop yield prediction is influenced by two primary groups of features. The first group includes factors such as land use, soil management, fertilizer application, and irrigation methods, all of which are determined by the farmer. The second group comprises environmental factors like temperature, rainfall, and solar radiation, which are governed by natural conditions (Maya Gopal & Bhargavi, 2019). Some of these key features will be discussed in the following sections.

2.5.1. Climate data

The productivity of agriculture is significantly affected by various climate variables such as precipitation, air temperature, humidity, and solar radiation, posing challenges for food security in regions prone to droughts or other weather-related disasters (Abbas et al., 2020). Seasonal variability in precipitation and temperature can lead to substantial reductions in crop yield (Lobell & Field, 2007). The impact of climate change on potato agriculture is increasingly crucial, with rising temperatures potentially restricting potato cultivation to higher elevations in warmer regions, as tuber growth is impeded above 33°C, and maintaining adequate water supply of over 500 mm during the typical 120–150 day growing season becomes essential for achieving respectable yields (Jennings et al., 2020). Presently, there is a growing focus on utilizing a range of crop–weather models to evaluate how changes in climate impact potato crop development. For instance, a study by Adekanmbi et al. (2023) was conducted to evaluate the future impacts of climate change on potato yields in PEI under various climate scenarios, informing the development of effective adaptation strategies for sustainable potato production in the region. Water availability in soil is a critical environmental factor influencing plant growth and development. Despite plants

evolving molecular mechanisms to minimize resource consumption and adapt to adverse conditions, water stress and deficits continue to present a significant challenge to agricultural productivity (Osakabe et al., 2014). Research on Europe's extreme weather impact identified rainfall and air temperature thresholds as the most reliable predictors of agricultural production (Beillouin et al., 2020). Ninanya et al. (2021) demonstrated that incorporating potato canopy temperature into a radiation use efficiency model significantly enhanced the prediction of tuber yield under varying water conditions, highlighting its value as an important indicator of plant response in different soil moisture contexts for future simulations. Kuradusenge et al. (2023) found that among RF, Polynomial Regression, and SVR models, RF performed best ($R^2=0.88$) in predicting potato yield using historical temperature and rainfall data.

2.5.2. Soil data

The spatial variability of soils, influenced by diverse physical, chemical, and biological processes operating at varying intensities and scales, directly affects plant growth and environmental conditions, necessitating precise understanding of soil properties for effective agricultural input management (Awal et al., 2019). The yield of potato tubers is influenced by soil physical, hydrological, and chemical properties (Zare et al., 2019). Farooque et al. (2020) used on-the-go proximal soil sensing to map soil electrical conductivity (ECa) and forecast potato tuber yield in Atlantic Canada, with results demonstrating strong correlations ($R^2=0.57-0.66$) between ECa and tuber yield variability, supporting the development of PA techniques for yield forecasting. In another study, Abrougui et al. (2019) assessed tillage methods' effects on soil properties and crop yield, concluding that the ANN model exhibited superior capability in relating potato yield to tillage and soil properties. Cation-exchange capacity (CEC) is another important soil metric that reflects the soil's ability to retain and provide essential cationic nutrients, such as calcium,

magnesium, potassium, and ammonium, to plants in addition to the soil's water-holding capacity (Manrique et al., 1991). Miao et al. (2006) investigated maize yield forecasting in eastern Illinois, USA, using ANNs. Their findings revealed that CEC plays a significant role among soil factors in the yield prediction models.

2.5.3. Agrotechnical traits

Agrotechnical features refer to different methods of potato cultivation, including mineral and organic fertilization, tillage, irrigation, plant protection, and crop rotation (Kurek et al., 2023). Adequate and timely fertilization with mineral and organic nutrients is essential for addressing environmental deficiencies, supporting optimal plant growth, and preventing nutrient-related disruptions that can adversely affect yield (Hara et al., 2021). For example, Niedbała (2019) developed a multilayer perceptron artificial neural network for pre-harvest winter rapeseed yield prediction using meteorological and mineral fertilization variables, achieving a MAPE of 9.43%; sensitivity analysis showed that weather variables ranked highest, while fertilization variables remained part of the predictive feature set.

2.5.4. Remote sensing data

The adoption of RS and spectroscopy tools during phenotypic data acquisition is becoming increasingly critical in effectively managing potato cultivation and developing reliable predictive models based on plant spectral characteristics. Accurate monitoring of potato crop N status requires rapid and cost-effective approaches, such as leaf spectral reflectance, which has shown strong potential for estimating leaf N content, with reported PLSR performance of $R^2 = 0.95$ and RPD = 4.3 for calibration, and $R^2 = 0.89$ and RPD = 2.5 for independent validation (Rawal et al., 2024). The upcoming sections of this paper will delve into essential aspects of potato spectral analysis, with a particular emphasis on studies conducted in the Canadian Prairies.

2.6. An overview of plant spectrum in response to nitrogen deficiency

Spectral analysis technology is instrumental in monitoring crop growth and diagnosing agronomic parameters effectively (R. Zhao et al., 2021). To accurately identify the N status in plants, it is crucial to comprehend the plant spectrum pattern and select sensors that effectively capture their reflectance. The spectral response under crop N stress varies significantly, and while analysing original hyperspectral data is intuitive for N RS assessment, the specific sensitive bands identified can differ for the same or different crops across various geographical environments (J. Zheng et al., 2022).

Healthy leaves absorb most of the incident ultraviolet light (UV) (100–400 nm) (H. Liu & Chahl, 2018). The visible (VIS) light spectrum (400–700 nm) reflectance is influenced by leaf pigments like chlorophyll or carotenoids (J.-T. Guo et al., 2017). The visible RGB cameras capture light in red (564–580 nm), green (534–545 nm), and blue (420–440 nm) spectral bands, mirroring human vision, and are extensively developed and commercially available with diverse features, making them popular for crop trait characterization due to their high spatial-resolution imaging and adaptability (C. Sun et al., 2022). After chlorophyll absorbs incoming photosynthetically active radiation, the majority of this energy is utilised for photosynthesis, with a small fraction re-emitted as chlorophyll fluorescence (Z. Li et al., 2020; Y. Zhang et al., 2018). Nitrogen deficiency in green vegetation reduces leaf chlorophyll content, thereby increasing canopy reflectance in the visible region, because N constitutes approximately 6% of chlorophyll by mass (Herrmann et al., 2010).

The infrared (IR) spectrum is divided into near-infrared (NIR 700–1,000 nm), short-wave infrared (SWIR 1,000–2,500 nm), middle-wave infrared (MWIR 3,000–5,000 nm), and long-wave infrared (LWIR 8,000–12,000 nm) (H. Liu et al., 2020a). Importantly, the weak chlorophyll fluorescence signals emitted overlap with leaf reflectance in the red and red-edge spectral region, typically

between 650 and 800 nm (W. Liu et al., 2019). In the NIR spectrum, the slope and position of the 'red edge'—located between the red absorption feature and high NIR reflectance—hold significant features for plant assessment (H. Liu et al., 2014). For instance, when plants experience N deficiency, red edge alters its shape and position (Cohen et al., 2010).

VIS-NIR spectroscopy, utilised extensively in agriculture, correlates chlorophyll content and photosynthetic potential of crops by analysing characteristic absorption bands in the blue, green, red, and red-edge regions (Wen et al., 2019). The study by Peanusaha et al., (2024) revealed that protein, identified as a trait within the radiative transfer models, exhibits significant promise as a predictor of N. In addition, Féret et al. (2021) determined that the most accurate estimation of leaf protein content at the leaf scale was achieved by utilizing two narrow spectral ranges: between 2100 and 2139 nm, and between 2160 and 2179 nm. The MWIR and LWIR regions, known as thermal IR, are valuable for assessing temperature-related aspects of plants, including water content and crop evapotranspiration (ET_c) (Berger et al., 2010). Reflectance in the SWIR region is primarily influenced by the absorption of water and the protein content of plants (Asaari et al., 2018). Multi- and hyper-spectral cameras provide more detailed spectral information compared to RGB cameras, with multispectral cameras capturing a limited number of discrete wavebands in the VIS-NIR range, and hyperspectral cameras generating 3D hyperspectral cubes containing both spectral and spatial information for each image pixel (C. Sun et al., 2022). There is limited research on using 350–2500 nm reflectance spectra for determining leaf N content in potatoes, particularly with fresh, intact leaves and various conditions such as potato varieties, maturity classes, growth stages, management practices, and environmental factors (Rawal et al., 2024). Increased N rates generally led to elevated LAI, consequently boosting the absorption of chlorophyll, water, and dry matter in both the VIS-to-NIR and SWIR regions (Jensen, 2009). N. Liu et al. (2021) demonstrated

that in the VIS and SWIR regions, reflectance decreased with an increase in N rates, while in the NIR region, reflectance increased with the total N fertilizer applied at the time of imaging.

VIIs derived from crop canopy spectral reflectance are commonly employed to monitor crop N status, and advances in hyperspectral techniques have enabled the exploration of more effective indices (F. Guo et al., 2023a). In recent decades, many studies have predominantly utilised basic parametric regression techniques centred on narrow-band VIIs like the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Red Edge Index (NDRE) for their analysis (Peanusaha et al., 2024). Mukiibi et al. (2024) systematically reviewed RS applications for potato growth monitoring and tuber yield prediction and reported that satellite imagery was most commonly used for yield prediction, whereas UAVs and handheld sensors were more frequently used for growth monitoring. They identified NDVI, Clred-edge, Cl green, and OSAVI as the most frequently used VIIs, with tuber initiation reported as the most suitable stage for RS data acquisition. In another study, Singha and Swain (2023) conducted a study using different crop VIIs to estimate potato crop yield with Sentinel-2B images, revealing a strong correlation between observed canopy reflectance and plant signals, particularly with the NDVI and Soil-Adjusted Vegetation Index (SAVI) data collected. Crop N status assessments primarily use the VIS spectrum (400-780 nm) with the occasional inclusion of NIR wavebands (800-980 nm), while specific bands like 1510 nm and 1676 nm are rarely utilised (Fu et al., 2021). The spectral reflectance of a canopy, influenced by factors like chlorophyll and N concentration, is also impacted by AGB and LAI, posing challenges in estimating crop N concentration using VIIs (Z. Zhou et al., 2018a).

The effectiveness of waveband combinations and formula formats in enhancing the accuracy of hyperspectral indices for assessing crop N status is subject to variability influenced by factors such as site conditions, annual variations, stages of crop growth, and specific cultivars (H. Yang et al.,

2021a). VI-based techniques typically utilise only a limited subset, 2–3 spectral bands of the entire spectrum, thus missing out on the valuable additional spectral data available across other wavelengths that could potentially explain the various discrepancies observed (N. Liu et al., 2021).

2.7. Advancements for precision agriculture in Canada

Precision agriculture integrates proximal and RS technologies with Internet of Things (IoT) sensors to monitor crop conditions across growth stages. This involves extensive data acquisition and processing related to crop health, enabling precise determination of specific parameters, their spatial distribution, and the optimal quantities required for healthy crops at specific times (Saha et al., 2018). Agricultural monitoring plays a crucial role in PA by enabling the tracking of crop health, the generation of variable prescription maps, the early identification of crop issues, and the implementation of timely remedial measures to minimize crop losses (Farooque et al., 2023). RS can predict tuber growth and yield by correlating aboveground traits with underground tuber characteristics (C. Sun et al., 2022). Proximal and RS technologies demonstrate the potential for monitoring spatial and temporal variability in crop growth, aiding in situ field N management decisions (D. Wang et al., 2024). RS technologies across ground-based, UAV-based, and satellite-based platforms are advancing in agriculture, with each platform offering distinct monitoring advantages and complementary strengths across spatial and temporal scales. Physiological traits like chlorophyll content, N concentration, and water status, which are difficult to assess visually, can be detected through variations in light spectrum reflectance (M. Yang et al., 2020). Information-based PA has demonstrated successful applications in investigating potato crop traits and field phenotyping in recent years (Fortin et al., 2011; Franceschini et al., 2017; Pei et al., 2019). A review by Sun et al. (2022) was done to summarize the applications of RS technologies for

precision potato trait characterization, providing updated knowledge and guidance for agronomists and farmers.

2.7.1. Spaceborne platforms

Since the 1970s, satellite-based RS has been widely used in agriculture for tasks like flood monitoring, yield prediction, crop identification, and land use assessment, gaining popularity due to improved sensor resolution, data frequency, accessibility, and availability over time (C. Zhang et al., 2020). Moreover, satellites provide agricultural areas with spatially and temporally consistent information throughout the growing season, enabling comprehensive capture of the crop's lifecycle and spatial variability within each field, all at a low cost (Atzberger, 2013). As satellite missions advance to offer frequent observations across large areas, scientists in optical RS spectroscopy face the challenge of upscaling developed models from field to spaceborne sensors (K. Berger et al., 2020). The research conducted by McNairn et al. (2002) in MB, Canada, stands as the only study in the use of satellite imagery for analysing potatoes (along with a few other crops). The study showed that multitime RADARSAT-1 imagery could accurately distinguish crop types, particularly when images were acquired in late July to early August, during reproductive and seed-development stages when canopy structural differences were more distinct. Another study conducted by Imtiaz et al. (2023) in PEI, Canada, utilised satellite imagery to monitor potato ET_c , revealing a strong correlation between NDVI and crop coefficient values derived from Landsat 8, Sentinel-2A, and Planet imagery, with Sentinel-2A performing the best among the satellites ($R^2=0.88-0.89$) in the year 2022. Despite the extensive potato cultivation in Canada and the potential advantages of using satellite imagery for precise fertilizer management, there has been a notable absence of studies focused specifically on utilizing satellite imagery for potato crop analysis.

2.7.2. Airborne platforms

Interest has grown in the use of UAVs in agriculture in recent years, particularly for PA and surveying applications, where drones are used to monitor crops (Castellanos et al., 2020). UAV imaging technology offers superior temporal and spatial resolution compared to ground and satellite RS techniques, making it optimal for monitoring crop growth and estimating physicochemical parameters at the farm scale (Yue et al., 2021). The expanding UAV market and diverse applications in production agriculture—including weed detection, disease monitoring, crop biomass estimation, yield loss assessment, and plant phenotyping—highlight a rising opportunity to leverage sensors for informing producers about crop N status and its variability within fields, enabling data-driven N management decisions (Thompson & Puntel, 2020). Moreover, morphological parameters, including plant height and canopy cover, directly reflect crop growth and nutritional status within the crop (Y. Fan et al., 2022). For example, a study conducted by Martins et al. (2023) revealed a strong correlation between root depth and plant height measurements (>0.85), with a high consistency (>0.95) observed across in-field soil and relief variations, demonstrating the effectiveness of utilizing UAV-based multispectral digital elevation models for dynamic assessment of potato crop development. Research on the utilization of UAVs in potato farming in Canada has been limited thus far, with only a few studies conducted specifically in Eastern provinces of Canada. Several recent studies have explored various aspects of potato crops using UAVs, including crop health and monitoring, such as those conducted by Théau et al. (2020) and Fortin et al. (2014) in Quebec (QC), and Farooque et al. (2023) in PEI. However, there is currently a notable gap in studies focusing on nutrient and yield assessment using UAVs for Canadian potato farms.

2.7.3. Ground-based platforms

The implementation of Wireless Sensor Networks (WSNs) for data monitoring will enhance the efficiency of crop supervision by reducing data acquisition time (Saha et al., 2018). Furthermore, numerous studies have been conducted in the field of WSNs applied to agriculture (Abbasi et al., 2014; Goel & Bindal, 2018; Ojha et al., 2015). In recent years, there has been significant interest among scientists in exploring the potential of imaging spectroscopy for quickly assessing the quality of potato and sweet potato tubers in agriculture (Su & Xue, 2021). Moreover, ground-based RS of canopy spectral reflectance is extensively used in agriculture to measure crop N status, providing instant data for real-time N fertilization guidance, effectively improving NUE and yield recovery from N stress (Z. Zhou et al., 2018a). Full-spectrum reflectance from field spectrometry has been employed in various studies (e.g., Nigon et al. (2015)) to monitor potato plants at the individual-leaf level, utilizing continuous measurements across a broad range of wavelengths, contrasting with VIs that rely on predefined wavelengths (N. Liu et al., 2021). Since the year 2000, only a few studies have utilised ground-based sensors for potato crops (including nutrient assessment, yield prediction, and disease detection) in Canada, all of which were conducted in eastern Canada. For example, the most recent study conducted in New Brunswick (NB) by Abukmeil et al. (2022) showed promising potential for estimating potato plant macro and micronutrients using foliar spectral reflectance (400–2500 nm), revealing significant correlations between petiole chemical contents and leaf spectra, particularly in dried leaf analysis across specific wavebands (400–1100 nm for macronutrients and 400–2500 nm for micronutrients, with a notable common significant waveband at 1932 nm). In another study in QC, Morier et al. (2015) showed that hyperspectral VIs derived from red-edge spectral reflectance demonstrated strong potential for assessing potato crop N status and predicting tuber yield variability during different

growth stages. Another study conducted in PEI and NB evaluated various ML algorithms, such as LR, elastic net (EN), k-nearest neighbor (k-NN), and SVR, for predicting potato yield using PS (Abbas et al., 2020). Their results indicated that SVM outperformed all other models in terms of yield prediction accuracy. However, in Western Canadian potato farms with varied climate and soil conditions, there is a notable lack of hyperspectral investigations utilizing field spectrometers or other ground-based sensors.

As shown in Table 2.1, a comprehensive overview of Canadian studies on advanced technologies for potato crop management since 2000 is provided. Research in Western Canada exploring the utilization of RS and ground-based technologies for potato nutrient management represents a novel and underdeveloped area of study. Despite the region's significant role in Canada's potato production, constituting over 40% of the nation's output (Statistics Canada, 2022), there remains a notable gap in research addressing this critical aspect of agricultural management.

Table 2.1. Research on advanced technologies for potato crop management in Canada since 2000.

Equipment	Applications	ML	Accuracy	Province	Reference
UAV	Crop height	-	-	QC	(Martins et al., 2023)
UAV	Vegetation monitoring	GAN (Pix2PixHD)	RMSE = 5.40–13.73; SSIM = 0.69–0.90 for Pix2PixHD	PEI	(Farooque et al., 2023)
Multiple satellites	ET _c mapping	-	-	PEI	(Imtiaz et al., 2023)
NIR analyser	Macro and micronutrient prediction	Lasso Regression	R ² =0.59 (for N)	NB	(Abukmeil et al., 2022)
Proximal sensors	Yield prediction	LR, EN, k-NN, SVR	Mean SVR RMSE = 5.84 t ha ⁻¹ ; range = 4.62–6.60 t ha ⁻¹	PEI - NB	(Abbas et al., 2020)
UAV	Crop scouting	LR, MLR	R ² =0.81 (for LR)	QC	(Théau et al., 2020)
Spectroradiometer	Disease detection	PLS-DA	PLS-DA overall accuracy = 91.11% at leaf level	Ontario	(Fernández et al., 2020)
Proximal sensor	Yield prediction	-	R ² = 0.57–0.66; RMSE = 12.2–18.3%	Atlantic provinces	(Farooque et al., 2020)
Spectroradiometer	Crop N status	-	-	QC	(Morier et al., 2015)
UAV	LAI patterns	MLP, LS-SVM	15%, 29%	QC	(Fortin et al., 2014)
proximal sensor	Yield prediction	NN, MLR	RMSE=0.67, 0.59	QC	(Fortin et al., 2011)
LAI handheld sensor	Tuber growth	NN	RMSE=483.2 kg ha ⁻¹	QC	(Fortin et al., 2008)
Spectroradiometer	N deficiency detection	-	-	QC	(M.-C. Bélanger et al., 2007)

Equipment	Applications	ML	Accuracy	Province	Reference
Spectroradiometer	Leaf chlorophyll and protein content	-	-	NB	(Botha et al., 2006)
Proximal sensors	N imbalance	-	-	QC	(M. C. Bélanger et al., 2005)
Satellite	crop condition and information	-	-	MB	(McNairn et al., 2002)

UAV: Unmanned aerial vehicle, QC: Quebec, GAN: Generative adversarial networks, PEI: Prince Edward Island, ET_c: Electrical conductivity, NIR: Near-infrared, NB: New Brunswick, LR: Linear regression, EN: Elastic net, K-NN: k-nearest neighbor, SVR: Support vector regression, MLR: Multiple linear regression, PLS-DA: Partial least square-discriminant analysis, N: Nitrogen, MLP: Multiple-layer perceptron, LS-SVM: Least squares support vector machine, NN: neural networks, and LAI: Leaf area index

2.8. Key challenges in advanced precision agriculture techniques

RS technology, whether employed via proximal, UAV, or satellite platforms, holds promise for PA in a rapidly advancing technological era; however, practical implementation requires cost-effectiveness, consistent farmer access to technology, and a balance between tool complexity, accuracy, and farmer usability, necessitating extensive end-user training efforts (Hunt Jr & Daughtry, 2018; Weiss et al., 2020). Ongoing developments in satellite platforms target the creation of new sensors with enhanced spectral and directional capabilities specifically for agricultural needs, while PS faces cost constraints and UAV utilization is heavily influenced by meteorological conditions, regulations, and technical limitations; additionally, ML approaches encounter challenges related to training database composition and the need to account for spatial and temporal variability, noise, and biases to ensure method generalizability and applicability (Weiss et al., 2020). Moreover, improving the precision of yield prediction models significantly

relies on the quality and reliability of input data encompassing weather, soil characteristics, and management practices, necessitating advancements in data acquisition and processing techniques, particularly in large-scale applications, to minimize uncertainties and optimise predictive outcomes (Lin et al., 2023). In addition to data collection, the processing and analysis of data pose significant challenges in estimating plant ecological parameters from UAV RS, with a key issue being the limited generality of prediction models due to dependencies on specific datasets, uncertainties in data collection and processing (notably radiometric correction), and variations in study areas, acquisition dates, and plant species (Z. Sun et al., 2021). Moreover, although ML algorithms offer significant advantages, they often emphasize enhancing regression accuracy by excessively fitting the model to a particular training dataset rather than effectively establishing a robust and consistent relationship between remotely sensed data and N levels, where overfitting results from the algorithm's deep learning of dataset-specific noise and fluctuations, leading it to become overly attuned to these nuances rather than the underlying data (Peanusaha et al., 2024).

2.9. Conclusion

The integration of agriculture with new technologies and ML algorithms can significantly enhance farmers' productivity and promote environmental sustainability. Globally, RS and PS technologies are widely utilised across various crops. However, in Canada, there remains a notable gap in applying these technologies to potato crops, which are cultivated extensively. Potatoes demand precise fertilizer application to optimise NUE. Leveraging advanced technologies for this purpose can lead to more efficient fertilizer use, improved crop yields, and reduced environmental impact. Addressing this gap could position Canada as a leader in sustainable potato farming by adopting innovative agricultural practices.

Utilizing UAV-LiDAR (light detection and ranging) technology and multispectral optical sensors will facilitate the development of robust machine-learning models that provide valuable insights to farmers, field managers, and policymakers. Advancements in software, sensor integration, and data processing will support near real-time potato yield prediction while helping to reduce spatiotemporal limitations and costs associated with satellite data.

2.10. References

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Chapter 3

In-Season Potato Nitrogen Prediction Using Multispectral Drone Data and Machine Learning

3.1. Abstract

Assessing nitrogen (N) status in potato (*Solanum tuberosum* L.) during the growing season is crucial for optimising fertilizer application, aligning it with crop demand, and improving N use efficiency, particularly in Western Canada, where extensive potato cultivation supports the agricultural industry. This study evaluated the performance of three machine learning (ML) models—Random Forest (RF), Support Vector Machine (SVM), and Gradient Boosting Regression (GBR)—for predicting potato N status and examined the impact of feature selection techniques, including Partial Least Squares Regression (PLSR), Boruta, and Recursive Feature Elimination (RFE). A field experiment was conducted in 2023 and 2024 near Carberry, Manitoba, Canada, with plots receiving different N rates from various fertilizer sources. Multispectral drone imagery was collected throughout the growing seasons, and key vegetation indices (VIs) related to plant N concentration were extracted for model training. Among the VIs, CI green exhibited the highest correlation with petiole NO_3^- -N concentration (PNC). The results indicate that RF outperformed SVM and GBR, achieving the highest coefficient of determination ($R^2 = 0.571$) and the lowest mean absolute error ($\text{MAE} = 0.365\%$) using the RFE feature selection method. Feature selection enhanced model performance in specific cases, notably RF with RFE, and both SVM and GBR with Boruta. These findings highlight the potential of ML-based approaches for in-season potato N monitoring and emphasize the importance of feature selection in enhancing predictive accuracy.

3.2. Introduction

To meet future food demands driven by population growth without increasing cropland or environmental risks, potato, the fourth most important food crop, could play a crucial role

(Raigond et al., 2020b). A hectare of potatoes can generate two to four times the caloric output compared with the same area of grain crops (Aliche et al., 2018). However, maximizing potato productivity requires effective nitrogen (N) management, as N is the primary limiting nutrient in potato cropping systems (Muleta & Aga, 2019). Potato crops typically exhibit relatively low N uptake efficiency, ranging from 40% to 60% (Rens et al., 2018), partly because their shallow rooting system limits access to N beyond the main root zone and increases susceptibility to N losses through immobilization, volatilization, leaching, and runoff, especially under poor agronomic practices (Gitari et al., 2018). Insufficient N causes early canopy senescence and reduced yield, whereas excessive N leads to excessive vine growth, reduced tuber yield, and delayed maturity (Alkhaled et al., 2023). Therefore, a well-planned N fertilizer application strategy supports the normal growth of potato plants and prevents increased production costs and environmental pollution from excessive N, which is crucial for the sustainable development of the potato industry (Y. Fan et al., 2023).

Petiole NO_3^- -N concentration (PNC) is currently used to guide N fertilizer applications in potato production, but this approach is limited by point sampling and does not capture fine-scale spatial variability within the field (Nigon et al., 2015). To address this limitation, precision farming has gained attention for its ability to manage crop and soil variability at a finer scale, helping farmers optimise yield, reduce costs, and increase profitability (Paustian & Theuvsen, 2017). Remote sensing (RS) offers a cost-effective, non-destructive method to estimate plant N concentration by analysing canopy reflectance, which is influenced by chlorophyll levels, thus improving nutrient management by addressing spatio-temporal variability (J. Peng et al., 2021b). Chlorophyll content, as a key indicator of photosynthetic activity, is closely related to N concentration in green vegetation and has therefore been widely used as an indirect proxy for assessing plant N status

(Haboudane et al., 2002). Unmanned aerial vehicles (UAVs), also known as drones, are valuable in RS for precision agriculture (PA), providing high-resolution data that are crucial for monitoring N status (Hunt et al., 2018; Khot et al., 2016). Drones, as a type of UAV, offer distinct advantages in PA by providing high-resolution multispectral imagery with greater flexibility in timing compared with manned aircraft (J. Zhang et al., 2024). A study conducted in Denmark showed that UAV-based multispectral data outperformed satellite (Sentinel-2) and handheld (RapidScan) sensors in assessing potato N status, primarily due to the higher spatial resolution of the UAV images (J. Peng et al., 2021b). Potato leaf chlorophyll content could be reliably estimated using reflectance near the 700 nm red-edge position, achieving an R^2 value of approximately 0.86 (T. Zheng et al., 2018). Spectral reflectance-based vegetation indices (VIs) from crop canopies are widely used in RS to monitor N content in crops (F. Guo et al., 2023b). VIs are created to emphasize specific characteristics of vegetation while minimizing the influence of other factors (Verrelst et al., 2015). Numerous VIs (including ratio, normalization, and derivative indices) and crop growth indices (such as crop N/chlorophyll concentration, crop N/chlorophyll accumulation, leaf area index (LAI), and biomass) have been developed globally to diagnose crop N status by identifying sensitive bands in the canopy reflectance spectrum (B. Zhao et al., 2018). Among these VIs, the ratio vegetation index (RVI) and Normalized Difference Vegetation Index (NDVI) are the most common (Yao et al., 2010). UAV monitoring has been used to assess the N status of Ranger Russet potatoes across N rates from 0 to 449 kg ha⁻¹, demonstrating that NDVI can predict leaf chlorophyll content with an R^2 of up to 0.85. However, NDVI often saturates at high canopy densities due to red reflectance saturation (Hunt et al., 2018). Red edge-based VIs are resistant to saturation and provide reliable information on crop chlorophyll and N concentrations (Z. Zhou et al., 2018b).

The primary goal of PA in cropping systems is to enhance decision-making by providing spatial and temporal information, enabling targeted management of plant health and nutrient status (Chlingaryan et al., 2018). Machine learning (ML) offers a valuable and supplementary method to crop simulation models by integrating a range of factors affecting crop growth, bypassing the need for intricate plant physiological details (J. Jiang et al., 2022). ML resolves complex nonlinear problems by integrating data from multiple sources, as evidenced by its successful application to agricultural RS inversion (Zha et al., 2020). Effective N management necessitates a robust correlation between RS data and crop N status, and Random Forest (RF) provides a flexible, non-parametric approach that avoids overfitting and is simpler compared with other methods like artificial neural networks (J. Peng et al., 2021b). Several studies have compared various ML models for predicting N levels in crops, consistently finding that RF delivers superior performance (Osco et al., 2020; Tang et al., 2024b; H. Yang et al., 2023). The Support Vector Machine (SVM) is another widely used ML approach for N status prediction. SVM has been successfully applied in agricultural research, such as predicting soil moisture and nitrate-N content in time-series data (S. Yang & Huang, 2009), estimating canopy N weight in corn using UAV multispectral images (Lee et al., 2020), and evaluating soil nutrient levels alongside artificial neural networks (H. Li et al., 2014). Gradient Boosting is another ensemble learning technique that sequentially builds weak learners to minimize errors. While Gradient Boosting has been widely applied in agricultural modelling tasks such as yield prediction (Huber et al., 2022; Pradeep et al., 2023), studies focusing specifically on N status prediction remain limited.

A critical scientific question in PA is how to optimise ML models for accurate and efficient prediction of PNC using high-resolution remote sensing data. Feature selection in ML algorithms helps reduce data redundancy and prevent overfitting, thereby enhancing the accuracy of

predictions for crop parameters such as yield and leaf chlorophyll concentration (Fei et al., 2022). The process of feature selection involves choosing a subset of the original features by evaluating their importance, aiming to enhance both model performance and interpretability (Uğuz, 2011).

Despite growing interest in UAV-based remote sensing and ML approaches for crop N management, few studies have comprehensively evaluated the effectiveness of different ML models and feature selection techniques for in-season potato N prediction using high-resolution drone imagery. In particular, as reviewed in Chapter 2, research focused on Canadian agroecosystems remains limited, despite the importance of site-specific nutrient management strategies under spatially variable soil and climate conditions. In addition, our study introduces a broader spectrum of N management strategies compared with previous research. By incorporating 15 distinct N fertilization treatments, including various rates, sources, and application timings, we aimed to capture a wider range of in-field N variability. This diversity improves model learning and allows for more nuanced exploration of the relationship between RS signals and PNC. This study addresses this gap by (1) investigating the relationships between drone-derived VIs (as proxies for chlorophyll content) and PNC in potato, (2) developing and comparing the performance of three supervised ML models (RF, SVM, and Gradient Boosting Regression (GBR)) for predicting in-season PNC using high-resolution multispectral imagery, and (3) systematically evaluating the effectiveness of three distinct feature selection techniques—Partial Least Squares Regression (PLSR), Boruta, and Recursive Feature Elimination (RFE)—in improving model accuracy and interpretability across various ML algorithms. By achieving these objectives, this research aimed to improve N management in potato cultivation through PA in Western Canada. Furthermore, the drone-based modelling framework developed in this study provides a scalable

pathway for applying similar methodologies to large-scale nutrient monitoring using high-resolution satellite imagery across diverse agricultural systems.

3.3. Materials and methods

To illustrate the comprehensive approach of this research, Figure 3.1 provides a schematic representation of the study's workflow. This flowchart details the sequence of the methodologies employed, including data acquisition and the supervised ML approaches utilised for N status prediction.

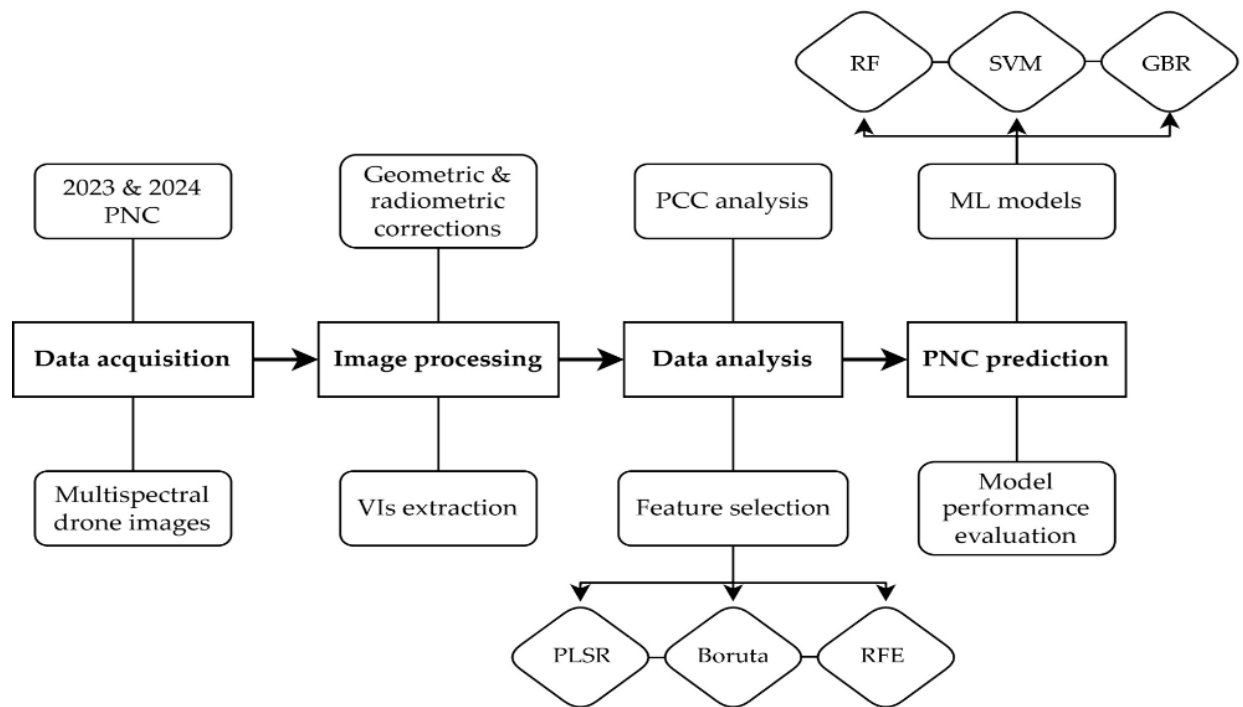


Figure 3.1. Workflow for petiole NO₃-N concentration (PNC) prediction using multispectral drone imagery and machine learning (ML). PCC, Pearson's correlation coefficient; PLSR: Partial Least Squares Regression; RFE, Recursive Feature Elimination; RF, Random Forest; SVM, Support Vector Machine; GBR, Gradient Boosting Regressor; VIs, vegetation indices.

3.3.1. Study area and field trials

The experiment was carried out during the 2023 (49°55'53.33"N, 99°23'21.20"W) and 2024 (49°55'53.85"N, 99°23'26.67"W) growing seasons in adjacent fields in Carberry, Manitoba (Figure 3.2). The primary crop rotation in this area includes wheat, canola, and potato. The study area is located in the prairie ecozone of Canada, part of North America's Great Plains. The climate in the region is characterized as a subhumid to semiarid, featuring short, warm summers and long, cold winters, with low levels of precipitation and high evaporation.

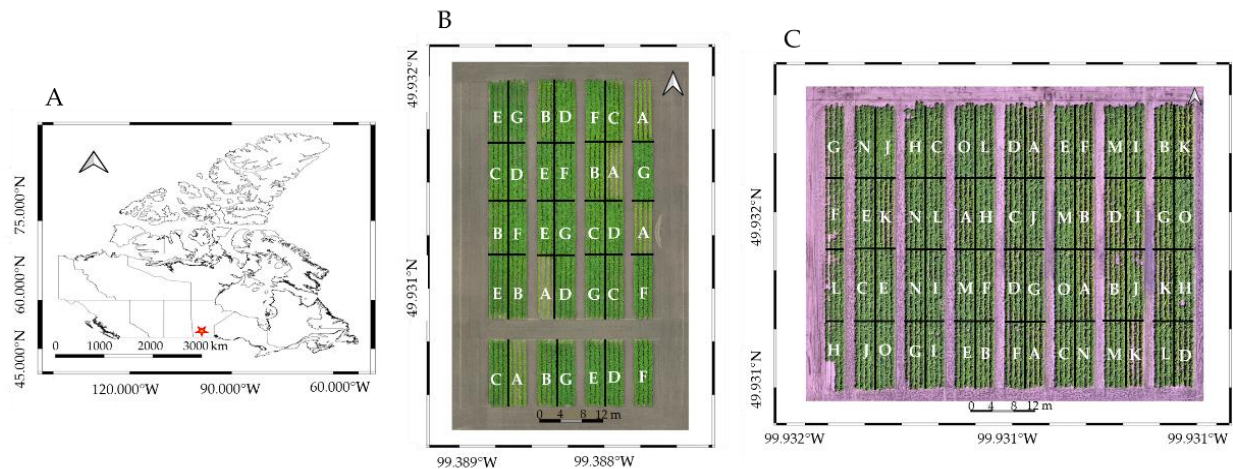


Figure 3.2. Study site and field trial layouts. (A) Location of the experimental site in Carberry, Manitoba, Canada, marked with a red “*”. (B) Plot arrangement for the 2023 field trial. (C) Plot arrangement for the 2024 field trial, with labeled plots (A, B, C, etc.) representing different nitrogen (N) treatment levels.

The experiment was designed using a Randomized Complete Block Design (RCBD) to randomly assign treatments to the experimental units, thereby minimizing potential bias. Each treatment plot measured 12 m in length and consisted of four rows, 4 m in width, with 1 m between rows. Russet Burbank, a leading potato cultivar in North America, widely cultivated and stored for both fresh market sales and frozen processing (Y. Wang et al., 2016), was used in this study.

In 2023, the crop was grown under six N fertilization treatments and 1 unfertilized control, with 5 replicates per treatment, totaling 35 experimental plots. This initial trial served as a preliminary

study to evaluate the feasibility of using UAV-based multispectral imaging for in-season PNC prediction. On the basis of the insights gained, the 2024 experiment was expanded to include 15 N fertilization treatments, each with 4 replicates, resulting in 60 experimental plots. This expansion allowed for a broader assessment of treatment effects and improved model robustness by capturing greater variability in plant responses. This study investigated N treatments using urea, environmentally smart N (ESN), ammonium sulfate (AS), and super urea (SuperU), applied at various rates and timings, including pre-planting and top-dressing, as detailed in Table 3.1.

Table 3.1. Nitrogen application rates and sources for the 2023 and 2024 field trials.

Treatment	2023		2024	
	Source	Rate (kg/ha)	Source	Rate (kg/ha)
A	Control	0	AS	105
B	ESN	112	Urea + AS *	168
C	ESN	168	Urea + AS	197
D	ESN	313	Urea + AS *	168
E	SuperU	112	Urea + AS	235
F	SuperU	168	ESN + AS	156
G	SuperU	313	SuperU + AS	156
H	-	-	ESN + AS *	235
I	-	-	ESN + AS *	235
J	-	-	SuperU + AS	235
K	-	-	Control	0
L	-	-	ESN	112
M	-	-	ESN	168
N	-	-	SuperU	112
O	-	-	SuperU	168

Fertilizer sources: environmentally smart nitrogen (ESN), ammonium sulfate (AS), urea, and SuperU (a stabilized urea containing urease and nitrification inhibitors). * In 2024, treatments B and D received the same pre-fertigation nutrient applications but differed in fertigation strategies, as they were part of separate experimental trials. Treatments H and I received the same total nitrogen rate by row closure; however, Treatment H received 70% at pre-planting and 30% at top-dressing, whereas Treatment I received the full amount at pre-planting.

Soil properties such as organic matter, pH, cation exchange capacity, and macronutrient concentrations of nitrogen (N), phosphorus (P), potassium (K), and sulfur (S) were analysed to characterize the experimental sites and are summarized in Table 3.2. All plots were provided with adequate irrigation and essential nutrients, including P, K, S, and calcium (Ca), to prevent nutrient deficiencies. Soil and petiole samples were collected using standardized procedures to ensure

consistency and representativeness across all plots. Soil samples were taken at standard depths commonly used for nutrient analysis. Petiole samples were collected at the row closure stage to assess plant nutrient status. The fourth petiole from the top of each plant was selected, leaflets were removed, and 30 petioles were collected per plot (not assigned individual geo-referencing) to ensure representative sampling of the plot, as recommended for potato nutrient monitoring (Westermann, 1993). The 30 petioles collected from each plot were pooled into a single composite sample for laboratory analysis, resulting in one PNC reference value for each plot. All samples were properly labeled and packaged for analysis at Agvise Laboratories (USA), where the soil and petiole samples were analysed for nutrient status using standardized laboratory protocols (D. A. Horneck, 2011).

Table 3.2. Soil analysis results for the experimental field before planting.

Parameters	Results	
	2023	2024
Texture	Sandy loam–sandy clay loam	Sandy loam–sandy clay loam
Organic matter	1.8%	1.7%
pH	5.4	6
Cation exchange capacity, mEq·L ⁻¹	8.4	8.4
Available N (0–30 cm), kg·ha ⁻¹	10.3	30.4
Available K (0–15 cm), mg kg ⁻¹	209	86
Available Olsen P (0–15 cm), mg kg ⁻¹	33	28
Available S (0–30 cm), kg·ha ⁻¹	30	84

3.3.2. Image acquisition and management

The multispectral images were captured 37 days after emergence in the 2023 growing season and 42 days after emergence in 2024, both during the vegetative growth phase. These imaging dates were aligned with petiole sampling to ensure consistency in data collection. The images were acquired under cloudless weather conditions using a DJI Mavic 3M drone (DJI Group, Ltd., Shenzhen, China), equipped with four 5MP multispectral cameras (green (G): 560 ± 16 nm; red (R): 650 ± 16 nm; red edge (RE): 730 ± 16 nm; near-infrared (NIR): 860 ± 26 nm) and a sunlight sensor to enhance the accuracy and consistency of the data under dynamic field conditions. Each camera has a native sensor resolution of approximately 4.4 mm per pixel.

To maximize image quality and spatial detail, all flights were conducted at a consistent altitude of 15 m above ground level, with a flight speed of approximately 5 m/s to minimize motion blur. The along-track (front) and cross-track (side) overlaps were set to 80% and 70%, respectively, to ensure comprehensive image coverage and enable accurate mosaicking. The camera was oriented at a

nadir (90° downward) angle for vertical image capture. Under these acquisition settings, the effective ground sampling distance (GSD) was approximately 1.27 cm/pixel for the multispectral imagery and 0.58 cm/pixel for RGB imagery. This distinction between the sensor's native resolution and the GSD reflects the influence of flight parameters on the spatial resolution of the ortho-mosaicked images used for analysis. For centimeter-precise results, the real-time kinematics (RTK REACH RS2+) provided accurate geolocation data for the drone imagery, ensuring precise field mapping and in situ measurements. The drone raster images were ortho-mosaicked using DJI Terra (version 3.9.4, DJI, Shenzhen, China).

3.3.3. VI extraction from multispectral images

Spectral VIs have been the primary and most commonly used method for estimating variable parameters (H. Yang et al., 2021b). In this study, 11 commonly used VIs were calculated using multispectral raster calculator tools in QGIS (version 3.28.3, QGIS Development Team, Open Source Geospatial Foundation, USA) (Table 3.3). For each plot, the average pixel value of each VI was calculated using manually drawn plot boundaries, ensuring that each VI represented the mean canopy reflectance within the defined area. These indices—NDVI, GNDVI, RNIR, GNIR, RVI, GRVI, SAVI, CI green, TCARI, MCARI, and SRRE—were selected according to their relevance in previous studies (S. Gao et al., 2024; Hunt Jr et al., 2013; Rodrigues et al., 2022).

Table 3.3. Extracted vegetation indices (VIs), used as proxies for chlorophyll content, to estimate petiole NO_3^- -N concentration (PNC) in potato crops.

VIs	Description	Formula	Reference
NDVI	Normalized Difference Vegetation Index	$\frac{(NIR - R)}{(NIR + R)}$	(Rouse et al., 1974)
GNDVI	Green Normalized Difference Vegetation Index	$\frac{(NIR - G)}{(NIR + G)}$	(A. A. Gitelson et al., 1996)
RNIR	Ratio between red and near-infrared	$\frac{R}{NIR}$	(Richardson & Wiegand, 1977)
GNIR	Ratio between green and near-Infrared	$\frac{G}{NIR}$	(Bausch & Duke, 1996)
RVI	Ratio vegetation index	$\frac{NIR}{R}$	(Zhu et al., 2008)
GRVI	Green ratio vegetation index	$\frac{(G - R)}{(G + R)}$	(D. E. Johnson et al., 2001)
SAVI	Soil adjusted vegetation index	$\frac{1.5(G - R)}{G + R + 0.5}$	(Huete, 1988)
CI green	Green chlorophyll index	$\frac{NIR}{G} - 1$	(A. A. Gitelson et al., 2003)
TCARI	Transformed chlorophyll absorption ratio index	$3((RE - R) - 0.2)(RE - G)\left(\frac{RE}{R}\right)$	(Haboudane et al., 2002)
MCARI	Modified chlorophyll absorption ratio index	$((NIR - R) - 0.2(NIR - G))\left(\frac{NIR}{R}\right)$	(Daughtry et al., 2000)
SRRE	Red-edge simple ratio	$\frac{NIR}{RE}$	[51]

3.3.4. Correlation analysis of VIs and N levels using Pearson's Correlation Coefficient (PCC)

To evaluate the relationships between various VIs and plant N levels, a PCC analysis was conducted. The PCC quantifies the linear correlation between two variables, calculated as

$$r_{xy} = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}}, \quad (1)$$

where r_{xy} is the PCC between variables x and y , x_i and y_i are individual data points, and $\bar{x}$ and $\bar{y}$ are the means of the variables. PCC values range from -1 to 1 , indicating a perfect negative correlation and a perfect positive correlation, respectively, with 0 indicating no correlation.

The analysis was used to identify and quantify the strength of the linear relationships between VIs and N levels. A heatmap of the correlation matrix, with the upper triangle masked, was created to highlight unique pairwise correlations, providing a clear overview of the interrelationships among the variables and aiding decision-making in the modelling process. Separate heatmaps were generated for each growing season (2023 and 2024) rather than combining data into a single matrix. This was carried out to account for interannual variability in environmental and agronomic conditions, which can significantly influence the relationship between VIs and PNC.

3.3.5. Feature selection for enhanced prediction accuracy

To improve the accuracy of plant N status predictions, PLSR, Boruta, and RFE were individually employed (using Jupyter Notebook (version 6.0.3) with Python (version 3.8.5)) to identify and eliminate VIs that contributed minimally to the prediction models. PLSR was used to reduce dimensionality, Boruta was applied to determine the most relevant features, and RFE was utilised for feature selection, ensuring that only the most significant VIs were retained. Although certain ML models—such as RF—are inherently capable of handling redundant or less informative features due to their internal feature selection mechanisms, we applied all three feature selection techniques (PLSR, Boruta, and RFE) uniformly across the ML models to allow for a consistent and comprehensive evaluation of their influence on model performance.

PLSR, a multivariate statistical technique, was employed to reduce the dimensionality of the VI dataset by projecting the original predictor variables onto a set of orthogonal latent components

that maximize the covariance with the response variable (PNC). This transformation enhances model robustness by minimizing collinearity and capturing the most relevant spectral features. The PLSR decomposition can be expressed as

$$X = TP^t + E, \quad (2)$$

where X is the matrix of predictor variables, T is the matrix of latent scores, P^t is the matrix of loadings, and E is the matrix of residuals. The optimal number of components was selected via 10-fold cross-validation based on the highest coefficient of determination (R^2). VIs with minimal explanatory power were identified and excluded to enhance model performance and interpretability (Wold et al., 2001).

Boruta is a feature selection algorithm that works by comparing the importance of each feature with that of randomly generated shadow features. It iteratively removes less relevant features and retains only the most significant ones. The algorithm evaluates feature importance using a RF classifier and determines which features are statistically significant by comparing their importance with the shadow features. The decision process can be represented as

$$Importance_i = RF_{Importance}(X_i), \quad (3)$$

where $Importance_i$ is the importance of the feature (X_i), and $RF_{Importance}$ represents the importance score from the RF model. Features with an importance score higher than the shadow features are retained, and irrelevant ones are discarded. Boruta's ability to identify important features helps improve the predictive accuracy of ML models for plant N status prediction (Kursa & Rudnicki, 2010).

RFE is a feature selection technique that recursively eliminates less important features on the basis of their contribution to model performance. It works by training a model, ranking the features according to their importance, and removing the least important feature in each iteration until the optimal subset is achieved. In this study, RFE was applied using RF as the base estimator to ensure that the feature ranking was based on Gini importance, consistent with the decision-tree-based structure used in Boruta selection. The RFE elimination process at each iteration t can be expressed as

$$X_j = \arg \min_{X_i \in F_t} I_t(X_i) \quad (4)$$

where F_t is the set of features at iteration t , and $I_t(X_i)$ is the importance of feature X_i . By recursively applying this process, RFE identifies the most influential features, which helps improve model accuracy and reduce overfitting (Guyon & Elisseeff, 2003).

3.3.6. Supervised ML approach for N status prediction

To enhance the prediction accuracy of plant N levels, three supervised ML models, RF, SVM, and GBR were employed. The dataset comprised 95 plot-level observations, each consisting of one composite PNC reference value and one set of plot-mean vegetation indices, including 35 observations from 2023 and 60 from 2024. To mitigate overfitting and ensure robust model evaluation, a 10-fold cross-validation approach was applied across the entire dataset. In this process, the model is trained on nine folds (serving as the training set) and tested on the remaining fold (acting as the validation set). This is repeated 10 times so that each data point is used for both training and validation. Such an approach yields unbiased out-of-fold predictions and provides a reliable estimate of the model's generalization performance. No separate test set was reserved; instead, the model evaluation was based entirely on cross-validation results. The models were

trained and tested using two distinct approaches: one involving all VIs and another after feature selection.

The RF model, an ensemble learning method, operates by constructing multiple decision trees during training and averaging their outputs for prediction. Mathematically, the RF prediction for N , $\hat{y}_{RF}$, can be expressed as

$$\hat{y}_{RF} = \frac{1}{T} \sum_{t=1}^T h_t(x), \quad (5)$$

where T is the total number of trees, and $h_t(x)$ represents the prediction from the t -th tree for input feature x (Rodriguez-Galiano et al., 2015).

The SVM model, though primarily designed for binary classification, can be seamlessly extended to regression problems, enhancing its applicability in various predictive modelling scenarios (Shao et al., 2012a). The SVM prediction for N , $\hat{y}_{SVM}$, can be represented as

$$\hat{y}_{SVM} = W^T x + b, \quad (6)$$

where W is the weight vector, x represents the feature vector, and b is the bias term (Smola & Schölkopf, 2004b).

The GBR model is a popular ML technique for regression tasks that combines multiple weak learners (typically decision trees) to form a strong predictive model (Friedman, 2001). The GBR prediction for N , $\hat{y}_{GBR}$, can be represented as

$$\hat{y}_{GBR} = F_0(x_i) + \sum_{t=1}^T \gamma_t h_t(x_i), \quad (7)$$

where F_0 is the initial model vector, $h_t(x_i)$ is the t -th weak learner (tree) applied to the input (x_i) , γ_t is the step size or learning rate for the t -th tree, and T is the number of trees (Hastie et al., 2008).

3.3.7. Model performance evaluation

The study compared model performance with and without reduction in the VIs to assess how dimensionality reduction affects the accuracy of N status prediction. This comparison provides valuable insights into which approach is better for selecting features to optimise N management in potato crops. During model evaluation, three metrics, namely the coefficient of determination (R^2), root mean squared error (RMSE), and mean absolute error (MAE), were used to compare the N content of plants predicted by the model with the measurements obtained in the field. It should be noted that these criteria have been commonly applied in earlier studies (El-Kenawy et al., 2024; Yin et al., 2023). R^2 , RMSE, and MAE were calculated with the following equations

$$R^2 = 1 - \frac{\sum_{i=1}^n (N_i^m - N_i^p)^2}{\sum_{i=1}^n (N_i^m - \bar{N}_i^m)^2}, \quad (8)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (N_i^m - N_i^p)^2} \quad (9)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |(N_i^m - N_i^p)| \quad (10)$$

where N_i^m represents the actual potato N data (%) of the i -th sample, $\bar{N}_i^m$ is the mean of the actual potato N data, N_i^p represents the potato N data (%) of the i -th sample predicted by the N estimation model, n is the sample size, and i is the sample number.

3.4. Results

3.4.1. PNC across treatments and growing years

The PNC varied across treatments, reflecting the influence of different N applications (Figure 3.3). The control treatments (A in 2023 and K in 2024) had the lowest PNC values, showing minimal variation among replicates. This confirms that plants in these plots relied solely on the native soil N, which was insufficient to support higher N accumulation. The narrow distribution of PNC values in these treatments suggests a consistent N deficiency across the plants.

In contrast, N-fertilized treatments exhibited a wider range of PNC values, with several treatments showing higher concentrations than the unfertilized controls. This variation likely reflects differences in N application rate and fertilizer source, as well as plot-level variability in plant response. Some treatments showed narrow PNC distributions, whereas others showed greater within-treatment variability, suggesting differences in treatment response among plots. The presence of outliers in multiple treatments suggests localized variability in soil fertility or differences in individual plant responses.

From a modelling perspective, the diversity in N concentrations across treatments is beneficial for training ML models. A well-distributed dataset, containing both low and high PNC values, ensures that the models can capture the full spectrum of N variability in plants. This improves the ability of predictive models to generalize across different conditions, making them more robust for real-world applications. Treatments with distinct N responses provide valuable data points for developing accurate models that can predict N status on the basis of RS inputs.

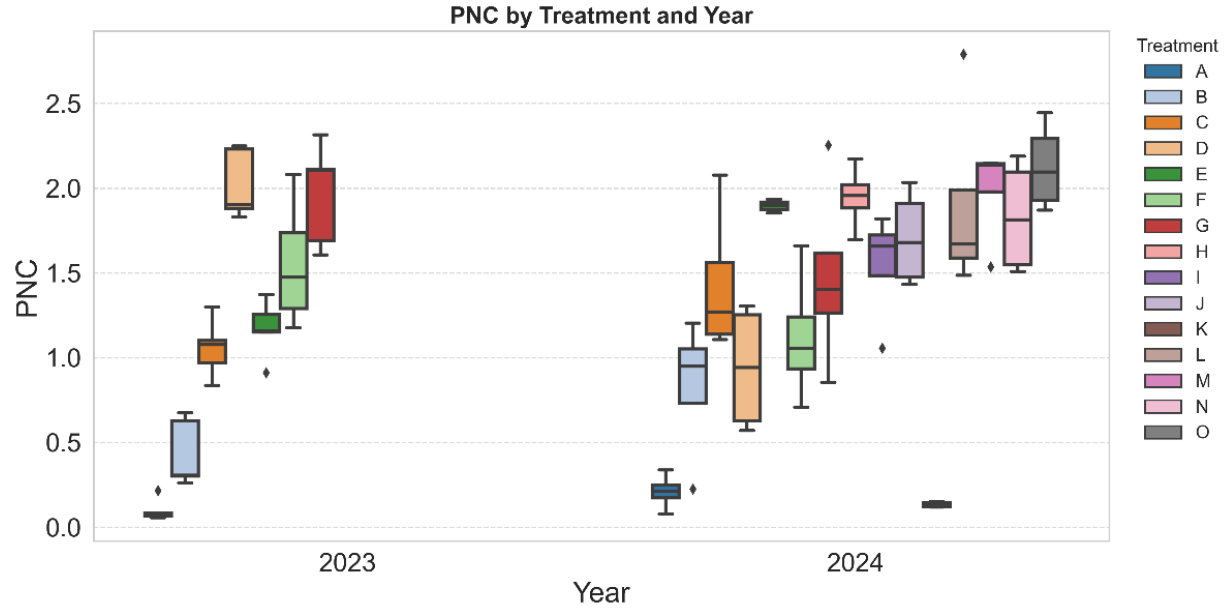


Figure 3.3. Distribution of petiole NO_3^- -N concentration (PNC) across treatments in 2023 and 2024. The boxplots display the variability in PNC, with the boxes representing the interquartile range (IQR) and the horizontal line inside each box indicating the median. Treatments correspond to the nitrogen fertilizer types and rates described in Table 3.1. Diamond-shaped points represent statistical outliers, defined as values below $Q1 - 1.5 \times \text{IQR}$ or above $Q3 + 1.5 \times \text{IQR}$.

3.4.2. Correlation analysis of VIs with PNC

The correlation analysis revealed that certain VIs maintained a strong relationship with PNC across both years (Figure 3.4). In 2023, CI green exhibited the highest correlation with PNC ($r = 0.75$), followed closely by GRVI ($r = 0.72$). Other indices, such as NDVI ($r = 0.64$) and GNDVI ($r = 0.63$), also showed moderate positive correlations, while GNIR and RNIR displayed negative associations, indicating an inverse relationship with PNC.

In 2024, the strongest correlations were observed with GNDVI ($r = 0.73$) and GNIR ($r = -0.73$), the latter showing a strong negative relationship with PNC. CI green ($r = 0.71$) and RNIR ($r = -0.71$) also exhibited high correlations, with RNIR again displaying a negative association. Notably, MCARI and TCARI showed relatively strong correlations at 0.67 and 0.63, respectively,

indicating their potential for PNC estimation. Although some indices varied in strength between years, the overall trends suggest that multiple VIs can serve as effective indicators of PNC.

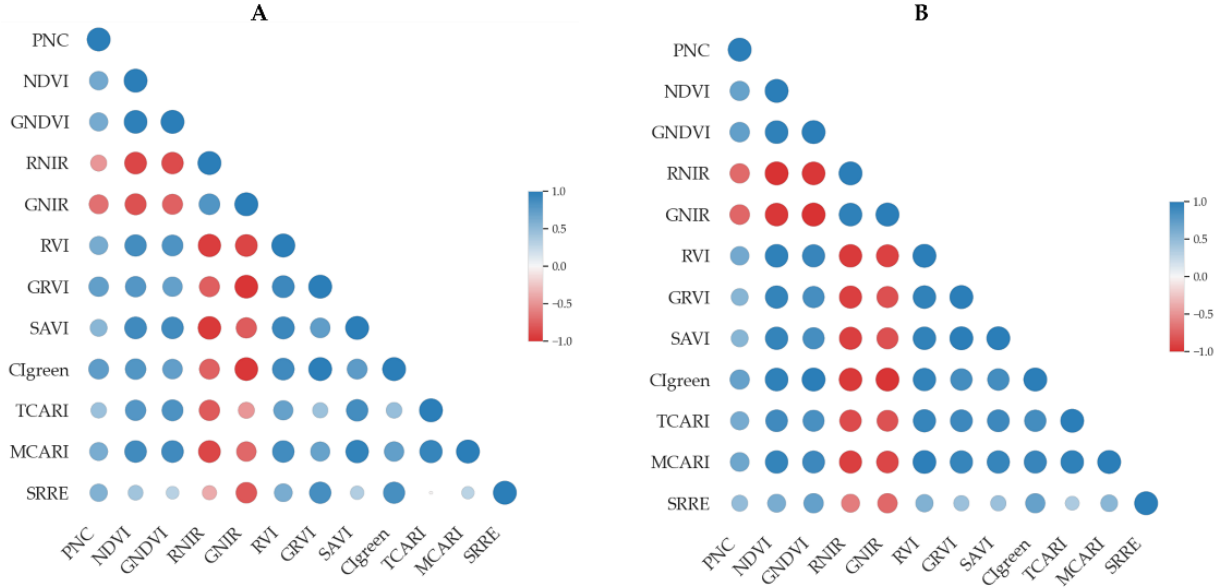


Figure 3.4. Pearson's correlation matrix among petiole $\text{NO}_3\text{-N}$ concentration (PNC) and vegetation indices (VIs). (A) Correlation matrix for the 2023 season; (B) correlation matrix for the 2024 season. The matrices show the strength and direction of linear relationships among PNC and spectral indices, as well as among spectral indices themselves. Inter-correlations among VIs are included to illustrate redundancy among indices derived from related spectral bands. Blue circles represent positive correlations, while red circles indicate negative correlations. The size and colour intensity of each circle reflect the magnitude of the Pearson correlation coefficient (r), with larger and more saturated circles denoting stronger correlations.

3.4.3. Feature selection for PNC prediction

Feature selection using PLSR, Boruta, and RFE identified subsets of VIs for predicting PNC. PLSR selected seven VIs, including NDVI, RNIR, and SAVI, among others. Boruta retained six VIs, such as GNDVI, GNIR, and GRVI. RFE identified five VIs, including GNDVI, GRVI, and CI green. All methods consistently selected CI green, TCARI, and MCARI, indicating their strong relevance for PNC prediction. The selected VIs are summarized in Table 3.4, with their impact on model performance evaluated in Section 3.4.4.

Table 3.4. Vegetation indices (VIs) selected for machine learning modelling by three feature selection methods: Partial Least Squares Regression (PLSR), Boruta, and Recursive Feature Elimination (RFE).

VIs	Feature selection method		
	PLSR	Boruta	RFE
NDVI	Selected	-	-
GNDVI	-	Selected	Selected
RNIR	Selected	-	-
GNIR	-	Selected	-
RVI	-	-	-
GRVI	-	Selected	Selected
SAVI	Selected	-	-
CI green	Selected	Selected	Selected
TCARI	Selected	Selected	Selected
MCARI	Selected	Selected	Selected
SRRE	Selected	-	-

3.4.4. Comparative assessment of N status prediction models

The performance of three ML models—RF, SVM, and GBR—was evaluated for PNC prediction using different feature selection methods, as shown in Figure 3.5. Scatter plots compare the actual and predicted values for each model, considering the original dataset and three feature selection techniques: PLSR, Boruta, and RFE. The RF model achieved the highest accuracy with features selected by RFE, whereas SVM and GBR performed best with features identified by the Boruta method.

RF predictions show that the original dataset yielded an R^2 of 0.564, an RMSE of 0.463%, and an MAE of 0.370%. PLSR decreased model performance ($R^2 = 0.550$, RMSE = 0.471%, MAE = 0.378%), indicating that some important features were likely discarded. In contrast, Boruta marginally improved the results compared with the original dataset ($R^2 = 0.569$, RMSE = 0.461%,

MAE = 0.366%). The best performance was achieved with RFE, which provided the highest R^2 (0.571) and the lowest MAE (0.365%), and a competitive RMSE, indicating that this method effectively retained the most relevant predictors for optimal predictive performance.

SVM results show that the original dataset resulted in an R^2 of 0.512, an RMSE of 0.490%, and an MAE of 0.386%. PLSR improved the model's performance, raising the R^2 to 0.520 and reducing the RMSE and MAE to 0.486% and 0.381%, respectively. Boruta achieved the best performance ($R^2 = 0.546$, RMSE = 0.472%, MAE = 0.371%), while RFE showed comparable performance ($R^2 = 0.544$, RMSE = 0.473%, MAE = 0.370%). Overall, Boruta provided a marginal advantage among the feature selection methods, although its performance was closely comparable to RFE.

GBR predictions reveal that the original dataset produced an R^2 of 0.530, an RMSE of 0.481%, and an MAE of 0.382%. PLSR led to a substantial drop in accuracy ($R^2 = 0.497$, RMSE = 0.498%, MAE = 0.400%), highlighting the loss of critical features. In contrast, Boruta improved the performance, achieving the best overall results ($R^2 = 0.569$, RMSE = 0.461%, MAE = 0.366%). RFE produced moderately weaker results ($R^2 = 0.541$, RMSE = 0.475%, MAE = 0.377%). These findings indicate that GBR's performance was highly sensitive to feature selection, with Boruta proving the most effective method.

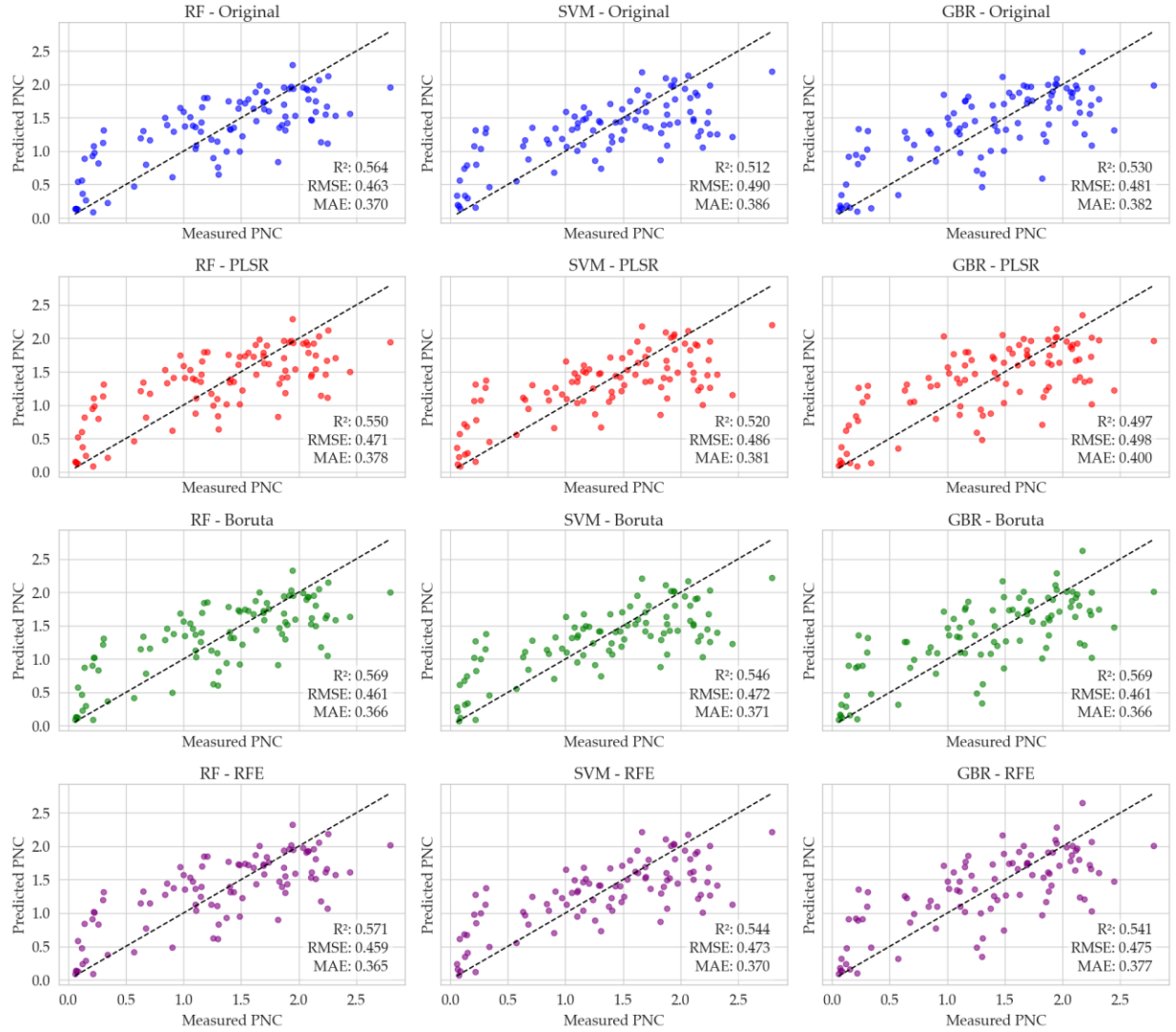


Figure 3.5. Scatter plots illustrating the relationship between actual and predicted petiole NO_3^- -N concentration (PNC) using three machine learning models: Random Forest (RF), Support Vector Machine (SVM), and Gradient Boosting Regressor (GBR). The black dashed line indicates the ideal 1:1 correspondence between the actual and predicted values. Model predictions are based on different feature selection methods: the original feature set (blue), Partial Least Squares Regression (PLSR) (red), Boruta (green), and Recursive Feature Elimination (RFE) (purple).

3.5. Discussion

The integration of UAV-based multispectral imagery with ML models presents a practical and adaptable framework for in-season PNC monitoring in potato crops, as evidenced by this study

conducted in Manitoba, Canada, during the 2023 and 2024 growing seasons. A key strength of this study lies in the inclusion of a broader and more diverse N treatment structure than that commonly reported in the literature. This expanded treatment range across multiple years improved the dynamic range of PNC in the dataset, thereby supporting more generalizable and accurate model development. By simulating practical nutrient management scenarios, the approach offers higher relevance for real-world PA applications. The results demonstrate that VIs, notably CI green and GNDVI, are strongly correlated with PNC, achieving Pearson correlation coefficients (r) of up to 0.75 and 0.73, respectively. The comparative analysis of ML models—RF, SVM, and GBR—paired with feature selection techniques (PLSR, Boruta, and RFE) highlights the robustness of model-specific preprocessing in enhancing predictive accuracy.

The strong correlations between CI green and PNC in both 2023 ($r = 0.75$) and 2024 ($r = 0.71$), alongside GNDVI in 2024 ($r = 0.73$), underscore their utility as proxies for N status. These findings align with studies demonstrating CI green's sensitivity to chlorophyll and N content in crops. For example, CI green was found to accurately estimate corn canopy N content ($R^2 = 0.91$, $RMSE = 0.63 \text{ g m}^{-2}$) due to its focus on green reflectance, which is strongly linked to the chlorophyll concentration (Salvador-Castillo et al., 2021). Similarly, CI green was identified as a key predictor of sugarcane leaf N, improving the accuracy of RF and SVM models (Soltanikazemi et al., 2022). The consistent selection of CI green, TCARI, and MCARI across all feature selection methods further supports their relevance, as these VIs capture spectral signatures associated with N-related physiological traits. However, the interannual variability in VI–PNC correlations (e.g., GNDVI's stronger correlation in 2024) suggests that environmental factors, such as soil properties or weather conditions, may influence VIs' performance, necessitating multi-season validation.

The superior performance of RF with RFE ($R^2 = 0.571$, $MAE = 0.365\%$) compared with SVM and GBR reflects RF's ability to handle nonlinear relationships and high-dimensional data, consistent with its widespread use in agricultural RS (Belgiu & Drăguț, 2016). RFE's effectiveness in optimising RF stems from its iterative elimination of low-importance features, retaining only those with high predictive power, such as CI green and GNDVI. This is consistent with findings that RFE enhanced RF-based alfalfa yield predictions by minimizing feature redundancy (L. Feng et al., 2020). Conversely, SVM and GBR performed best with Boruta ($R^2 = 0.546$ and 0.569 , respectively), likely because Boruta's feature importance ranking preserves the variables that complement their learning mechanisms. Our findings indicate that the integration of Boruta for feature selection enhances the performance of the SVM model, which aligns with previous research in the context of winter wheat yield prediction (Z. Li, Chen, et al., 2022). GBR's sensitivity to Boruta-selected features reflects its iterative error correction, which benefits from a curated feature set, as supported by studies on boosting models in agronomic applications (Friedman, 2001; Mahesh & Soundrapandiyan, 2024).

PLSR, however, reduced RF's and GBR's performance, likely due to its linear assumptions, which may discard nonlinear relationships that are critical for tree-based models. This contrasts with SVM, where PLSR improved performance ($R^2 = 0.520$), suggesting that SVM benefits from dimensionality reduction in high-collinearity datasets. These model-specific responses emphasize the need for tailored feature selection, as a one-size-fits-all approach can compromise accuracy. The observed variability in PNC across treatments provided a diverse dataset, enabling robust model training, but outliers in the fertilized plots indicate potential influences from soil heterogeneity or application timing, which warrant further investigation.

This study advances PA applications for Canadian potato production by using UAV imagery for site-specific N monitoring. However, limitations include the reliance on a limited number of spectral bands, which may constrain physiological insights compared with hyperspectral approaches (A. Khan et al., 2022). Despite the moderate R^2 values, the modelling framework demonstrated consistent, interpretable patterns aligned with crop physiology, offering practical value for mid-season N management and a foundation for more scalable applications. The dataset, while diverse (95 samples across two seasons), is relatively small, and the models' transferability to other agroecosystems remains untested. Interannual variability in soil properties and climate conditions may also affect VI–PNC relationships. Future research should explore the use of hyperspectral imaging to capture finer spectral details and integrate radiative transfer or crop growth models for enhanced physiological relevance (Baret et al., 2007; Houllès et al., 2004). Scaling the framework with larger, multi-regional datasets could support real-time decision-making tools, aligning with global efforts toward sustainable N management. Finally, incorporating temporal dynamics through time-series UAV data could improve model robustness by capturing N uptake patterns across growth stages.

3.6. Conclusion

This study examined the potential of integrating UAV-based multispectral imaging with ML models and feature selection techniques for in-season monitoring of PNC in potato crops. Over two growing seasons in Manitoba, VIs extracted from UAV imagery showed moderate to strong correlations with PNC, with CI green being consistently influential. Among the ML models tested, RF combined with RFE produced slightly better prediction metrics compared with the other model–feature selection pairings. SVM and GBR showed improved performance with the Boruta

technique. These results suggest that aligning feature selection methods with the structure of specific ML models can help improve predictive consistency.

While the findings are based on a limited dataset, they provide a practical framework that could be further explored in similar PA contexts. This approach may be applicable to other crops in the region but would benefit from additional validation across different conditions and scales. Rather than proposing a one-size-fits-all method, this study emphasizes the value of modest, model-specific adjustments in preprocessing and variable selection to support more informed nutrient management decisions using UAV imagery.

3.7. References

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Chapter 4

**VNIR-SWIR Hyperspectral Spectroscopy for
Nitrogen Assessment in Potato Crops: Deep
Learning and Regression Models Across Field
and Laboratory Conditions**

4.1. Abstract

Accurate evaluation of nitrogen (N) status is essential for optimising fertilizer application and sustaining yield in potato production systems. This study investigated the potential of Visible–Near Infrared to Short-Wave Infrared (VNIR-SWIR) hyperspectral reflectance spectroscopy for in-season prediction of petiole NO_3^- -N (PNN) under both field and laboratory conditions. Spectral data were collected from field canopies as well as from fresh and dried leaf tissues and analysed using three predictive approaches: One-Dimensional Convolutional Neural Network (1D-CNN), Support Vector Regression (SVR), and Partial Least Squares Regression (PLSR). Variable Importance in Projection (VIP) analysis was applied to identify key wavelength regions associated with N prediction across different measurement conditions. Among the tested models, 1D-CNN achieved the highest accuracy for laboratory fresh leaves with a coefficient of determination (R^2) of 0.90, root mean square error (RMSE) of 0.22 percent, and residual prediction deviation (RPD) of 3.18. SVR showed moderate accuracy, while PLSR exhibited the weakest predictive capability. Calibration transfer using Piecewise Direct Standardization (PDS) improved the performance of field-based models, increasing the R^2 from 0.77 to 0.82 for 1D-CNN and from 0.24 to 0.44 for SVR, confirming the effectiveness of spectral alignment for reducing environmental variability. Overall, laboratory-based fresh leaf spectroscopy provided more reliable N estimates than field and dried-tissue measurements, and the 1D-CNN outperformed SVR and PLSR models.

4.2. Introduction

The low utilization efficiency of nitrogen (N) fertilizers leads to substantial environmental losses, primarily through leaching and runoff, raising concerns in intensive crop production systems worldwide (Liang et al., 2019). Potato production, especially on the coarse-textured soils, faces

considerable risk of N loss through leaching, making precise fertilizer application essential to maintain yield and quality (X. Gao et al., 2018). Given that laboratory-based petiole NO_3^- -N analysis is time-consuming and reflects only the immediate N status, and leaf-based wet chemistry is labour-intensive and costly, proximal sensing of leaf traits offers a rapid, cost-effective, and integrative approach for assessing the cumulative N status of crops (Peddle et al., 2024; Rawal et al., 2024). Since the introduction of chlorophyll meters in the 1980s (Yadava, 1986), non-destructive proximal canopy reflectance sensors have advanced significantly and are now used to assess plant nutrient status and guide N fertilizer management across various crops (Lemaire et al., 2021).

Advances in precision agriculture, particularly the use of proximal sensing technologies, enable detailed field-scale assessment of spatial variability in N uptake; however, the full potential of these data acquisition methods remains underexploited (K. Wang et al., 2019). In plant nutrient analysis, spectroscopy enables the assessment of N status by detecting spectral patterns linked to pigments and molecular bonds, particularly those involving N in organic compounds like proteins and nucleic acids (Zahir et al., 2024). These spectral datasets provide the foundation for developing predictive models that translate reflectance patterns into indicators of crop N status. Each spectroscopy measurement produces a vector, referred to as a spectral signature, that captures the average intensity, reflectance, or transmittance within the lens's field of view (H. Liu et al., 2020b). The use of near-infrared (NIR) spectroscopy for N assessment has been extensively studied across various plant species including lettuce (H. Mao et al., 2015), winter oilseed rape (L. Li et al., 2016), bell pepper (Mishra et al., 2021), rice (Shao et al., 2012b), and wheat (Vigneau et al., 2011).

Spectral acquisition for plant nutrient assessment can be performed using three main methods: in-field canopy measurements, laboratory-based fresh-leaf scanning, and laboratory-based analysis

of dried, ground tissue. Laboratory spectroscopy has been widely adopted in plant nutrient assessment, as demonstrated by its application in recent studies (X. Miao et al., 2023; Rawal et al., 2024; Sharma et al., 2024), due to its ability to provide consistent and high-quality measurements under controlled conditions; however, it remains a destructive and time-intensive method, requiring extensive sample preparation steps such as leaf detachment, transport, drying, and grinding (Abukmeil et al., 2024). Environmental conditions such as temperature and time-related changes can introduce variability into NIR spectral datasets, which becomes embedded in multivariate calibration models and can impair prediction accuracy under new conditions. To correct for such environmental-induced spectral shifts, calibration transfer techniques such as Piecewise Direct Standardization (PDS) are commonly applied to align spectral data across different measurement settings (Ni et al., 2010).

Various approaches have been developed for predicting crop biochemical traits from spectral data, including classical linear multivariate methods, modern machine learning (ML) techniques, and more advanced deep learning (DL) architectures. In this study, we systematically compared the predictive performance of these three categories to evaluate their relative strengths for spectral-based prediction. ML provides a flexible framework for modelling complex agricultural data and has been successfully applied in tasks such as soil property estimation, yield prediction, and disease detection. DL extends these capabilities by employing multilayer architectures that automatically extract representative features from raw data, thereby enhancing prediction accuracy and adaptability (Durai & Shamili, 2022). Among DL models, convolutional neural networks (CNNs) are particularly effective due to their ability to automatically extract hierarchical features from input data through successive convolutional layers (Pourdarbani et al., 2021). In contrast, Support Vector Regression (SVR) represents a kernel-based ML method capable of capturing

complex nonlinear relationships between variables by mapping input data into a higher-dimensional space. It has been widely applied in agricultural and environmental studies for its robustness and reliable performance with limited or high-dimensional datasets (da Silva et al., 2024). Complementing these nonlinear approaches, Partial Least Squares Regression (PLSR) remains a widely used statistical method known for its ability to capture essential relationships within complex and interrelated data, providing a reliable basis for developing predictive models (X. Li et al., 2014). This capability has made PLSR a standard method in hyperspectral analysis and nutrient prediction, such as the estimation of soil total N using visible and near-infrared spectroscopy (T. Shi et al., 2013).

Despite the importance of nutrient management in potato systems, studies exploring the use of proximal sensing for N assessment in the Canadian Prairies remain limited, as reviewed in Chapter 2, highlighting a research gap in improving fertilizer efficiency in this major production region. While previous studies have utilised proximal sensing-derived vegetation indices to estimate N status in potato crops (Morier et al., 2015; Tang et al., 2024c; H. Yang et al., 2021b), the present study utilised the full hyperspectral reflectance spectrum, incorporating all available wavelengths rather than pre-defined indices. Most of these efforts have relied on laboratory-based spectral measurements (Rawal et al., 2024; Sharma et al., 2024) or in-situ field measurements (Gomez et al., 2024; Prikaziuk et al., 2022), with only a few studies integrating both approaches, such as one conducted on cotton (Xiao et al., 2022).

This study was designed to address these gaps through four primary objectives: (1) to identify key wavelengths within the VNIR-SWIR (350–2500 nm) spectrum that are most strongly associated with petiole NO_3^- -N concentrations; (2) to develop and compare DL, ML, and statistical regression models (1D-CNN, SVR, and PLSR) for predicting early-season N status from spectral reflectance

data; (3) to evaluate the influence of environmental (field) and controlled (laboratory, fresh vs. dried samples) conditions on the stability and transferability of spectral features relevant to N prediction; and (4) to assess the effectiveness of calibration transfer methods in harmonizing spectral data across measurement settings, thereby enhancing the accuracy and robustness of N prediction models under field conditions.

4.3. Data and methodology

4.3.1. Study area and sampling process

The field experiment was conducted in 2024 near Carberry, Manitoba, Canada (49°55'53.85"N, 99°23'26.67"W), in the Prairie ecozone of the northern Great Plains region. The region is characterized by a subhumid to semiarid climate with low annual precipitation, high evaporation, and a crop rotation system that typically includes wheat, canola, and potato. The experimental site featured sandy loam to sandy clay loam soils. The potato cultivar *Russet Burbank* was selected due to its commercial relevance and sensitivity to N management.

The study was arranged using a randomized complete block design (RCBD), with 15 N fertilization treatments applied in four replicates, resulting in a total of 60 plots. Each plot measured 12 m × 4 m (four rows spaced 1 m apart). The N treatments included four fertilizer types: Urea, Environmentally Smart N (ESN), Ammonium Sulfate (AS), and SuperUrea (SuperU). These were applied at different rates and timings, including pre-plant, top-dress, and split applications. Full details of the treatment structure, including fertilizer type, rate, and application timing, are provided in Table 4.1. All plots received uniform irrigation and supplemental nutrients to eliminate non-N nutrient limitations. Prior to planting, composite soil samples were collected from each plot. The average 2024 soil characteristics included an organic matter content of 1.7%, pH of 6.0, and

cation exchange capacity of 8.4 mEq L⁻¹. Available nutrient concentrations were 30.4 kg ha⁻¹ of nitrate-N (0–30 cm), 191.9 mg kg⁻¹ of potassium (0–15 cm), 61.9 mg kg⁻¹ of Olsen phosphorus (0–15 cm), and 84.2 kg ha⁻¹ of sulfate-sulfur (0–30 cm), indicating a moderately fertile profile.

Petiole tissue samples were collected at the row-closure stage, 60 days after planting, concurrent with spectral acquisition. In each plot, 30 petioles (the fourth from the top) were sampled following standardized nutrient monitoring guidelines (Westermann, 1993). For each plot, the 30 petioles were combined into one composite laboratory sample, yielding one PNN reference value per plot. Samples were labeled and submitted to Agvise Laboratories (North Dakota, USA), where they were analysed for macro- and micronutrient concentrations using standardized protocols (Horneck et al., 2011b). These field data provided the agronomic foundation for spectral analysis and model calibration.

Table 4.1. Summary of N fertilization treatments applied in the experiment.

Treatment	Source	Rate (kg/ha)
T1	AS	105
T2	Urea + AS *	168
T3	Urea + AS	197
T4	Urea + AS *	168
T5	Urea + AS	235
T6	ESN + AS	156
T7	SuperU + AS	156
T8	ESN + AS *	235
T9	ESN + AS *	235
T10	SuperU + AS	235
T11	Control	0
T12	ESN	112
T13	ESN	168
T14	SuperU	112
T15	SuperU	168

Fertilizer sources: Environmentally Smart Nitrogen (ESN); Ammonium Sulfate (AS); Urea; SuperU (a stabilized urea containing urease and nitrification inhibitors). * In 2024, treatments T2 and T4 received the same pre-fertigation nutrient applications but differed in fertigation strategies, as they were part of separate experimental trials. Treatments T8 and T9 received the same total nitrogen rate by row closure; however, treatment T8 received 70% at pre-planting and 30% at top-dress, whereas treatment T9 received the full amount at pre-planting.

4.3.2. Spectral data acquisition

Hyperspectral reflectance data were acquired in July 2024 using a full-range spectroradiometer (ASD FieldSpec Pro, Analytical Spectral Devices Inc., Boulder, USA) and a rugged Getac laptop. The instrument covered the spectral range from 350 to 2500 nm with a sampling interval of 1 nm, encompassing the VIS, NIR, and SWIR regions. The same system configuration, data acquisition software (RS³), and processing software (ViewSpec Pro v6.2; ASD Inc.) were used across all measurement conditions. Calibration was routinely performed using a certified Spectralon white

reference panel: every 5 minutes for field measurements and every 10 minutes during laboratory measurements. Absolute reflectance was calculated by adjusting the relative spectral dataset based on the known reflectivity of the white reference. For each plot and sample type, three replicate measurements were taken and averaged to produce a single representative spectrum. The field and laboratory measurement configurations are illustrated in Figure 4.1.



Figure 4.1. Hyperspectral reflectance data acquisition under field and laboratory conditions. (A) Canopy-level field measurements conducted under natural illumination. (B) Laboratory spectroscopy setup for leaf sample measurements under controlled illumination.

Field-based canopy reflectance measurements were conducted under clear skies and minimal wind, near solar noon to minimize shadowing effects. The spectroradiometer was positioned 30 cm above the canopy, perpendicular to the uppermost leaves. Three representative potato plants per plot were randomly selected, and their spectral datasets were averaged to produce a plot-level reflectance profile.

Additional laboratory measurements were performed on both fresh and dried leaf samples. From each plot, three fully expanded leaves with petioles were collected from the same canopies used for field-based spectral measurements, stored in sealed plastic bags at 4 °C, and transported to the University of Manitoba's Digital Agroecosystems Laboratory within two hours. For fresh tissue measurements, individual leaves were placed adaxial side up on a black non-reflective background

and scanned using the spectroradiometer connected to a fiberoptic cable. Illumination was provided by an external halogen lamp (12 VDC, 20 W) positioned approximately 10 cm above the sample surface. After scanning, the same leaves were oven-dried at 65 °C for 72 hours until a constant weight was reached, then ground using a ceramic mortar and pestle.

The powder was placed into petri dishes, leveled to create an even layer of approximately 2 mm, and scanned under the same halogen illumination used for fresh samples. Under the same external halogen lighting conditions, reflected light was collected using the fiberoptic cable mounted 3 cm above the sample at a 45° angle, with a 25° field of view targeting an effective sampling area of approximately 1.4 cm². All powdered samples were scanned using the same spectroradiometric and calibration setup as for the fresh and field measurements.

4.3.3. Spectral data preprocessing

Raw spectral data were preprocessed to enhance signal quality, reduce noise, and exclude wavelength regions affected by atmospheric interference or sensor limitations. The preprocessing pipeline consisted of three sequential techniques: Savitzky-Golay (SG) smoothing, Standard Normal Variate (SNV) transformation, and First Derivative (FD) transformation, implemented using Python (version 3.11) and the `scipy.signal` library.

SG smoothing was applied first to mitigate high-frequency noise while preserving spectral features. The SG filter was configured with a window length of 11 and a second-order polynomial, optimising the balance between noise reduction and signal fidelity (Savitzky & Golay, 1964; Schafer, 2011). Subsequently, SNV transformation was used to correct for multiplicative scattering effects by normalizing each spectrum to zero mean and unit variance. This was achieved by subtracting the mean and dividing by the standard deviation of each spectrum. Finally, FD transformation was computed using an SG filter (window length 11, polynomial order 2, first

derivative) to emphasize spectral shape, enhance absorption features, and reduce baseline offsets (Rinnan et al., 2009).

To ensure data quality, wavelength regions of 350–400 nm and 2350–2500 nm were excluded due to elevated noise near the spectral limits of the sensor, as observed in the raw reflectance data. In addition, the 1290–1500 nm and 1790–2050 nm regions were omitted because of strong atmospheric water vapor absorption, which interferes with surface reflectance signals (Curcio & Petty, 1951; N. Liu et al., 2021).

4.3.4. Identification of optimal wavelengths for N prediction

Selecting key wavelengths can yield models that are as accurate as, or superior to, those using the full spectral range, as they focus on the most informative spectral regions for predicting N while minimizing redundant data (L. Li et al., 2018). To identify wavelengths predictive of PNN, a PLSR model was employed, in combination with VIP analysis. Preprocessed spectral data were aligned with corresponding N concentrations measured from petiole samples. The PLSR model was configured with five latent components, and VIP scores were calculated to quantify the contribution of each wavelength to N prediction. Finally, several VIP threshold values were tested, and a threshold of 1.5 provided the best balance between model accuracy and feature reduction, retaining the most informative wavelengths while minimizing redundancy.

4.3.5. Development and evaluation of predictive models

Three regression models, namely 1D-CNN, SVR, and PLSR, were developed to estimate PNN from spectral reflectance data. Spectral inputs were limited to wavelengths with a VIP score ≥ 1.5 , identified through feature selection. Measured N concentrations were log-transformed before

calibration to stabilize variance and back-transformed for evaluation. All models were trained using identical datasets and evaluated on independent test sets to ensure a consistent comparison.

Each plot was treated as one experimental unit. For each measurement condition, the three within-plot spectra were averaged before modelling, and the resulting 60 plot-level observations were assigned to training ($n = 36$), validation ($n = 12$), and test ($n = 12$) subsets, with no plot represented in more than one subset. The 1D-CNN was employed to capture local spectral dependencies and extract discriminative features from reflectance data through convolution and pooling operations (Qin et al., 2025). The model architecture is shown in Figure 4.2. It consisted of one-dimensional convolutional layers with rectified linear unit (ReLU) activation functions, followed by max-pooling layers (pool size = 2) to reduce feature dimensionality. Extracted spectral features were flattened and passed through two fully connected layers for regression output. Weight decay regularization = $1.0E^{-4}$ and batch size = 15 were applied to mitigate overfitting. The 1D-CNN was trained using the predefined training, validation, and test splits, where the validation subset served the same purpose as cross-validation for tuning network hyperparameters and preventing overfitting. The dataset was randomly divided into training (60%), validation (20%), and testing (20%) subsets.

The SVR and PLSR models were trained and optimised using Randomized Search Cross-Validation (RandomizedSearchCV) with 5-fold cross-validation and three repetitions. SVR employed a radial basis function (RBF) kernel to model nonlinear relationships between spectral reflectance and PNN. The regularization parameter (C), kernel coefficient (γ), and loss tolerance (ϵ) were tuned to maximize predictive performance. All input features were scaled using RobustScaler to minimize the influence of outliers and illumination variability. The PLSR model, used as a linear benchmark, extracted latent components that maximized covariance between

spectral predictors and PNN. The optimal number of components (1–15) was selected to balance model complexity and accuracy. Model performance for all models was evaluated using the coefficient of determination (R^2), root mean square error (RMSE), and residual prediction deviation (RPD).

All data processing and model training were conducted on standard Windows-based computers using Python 3.11, with CPU-based computation.

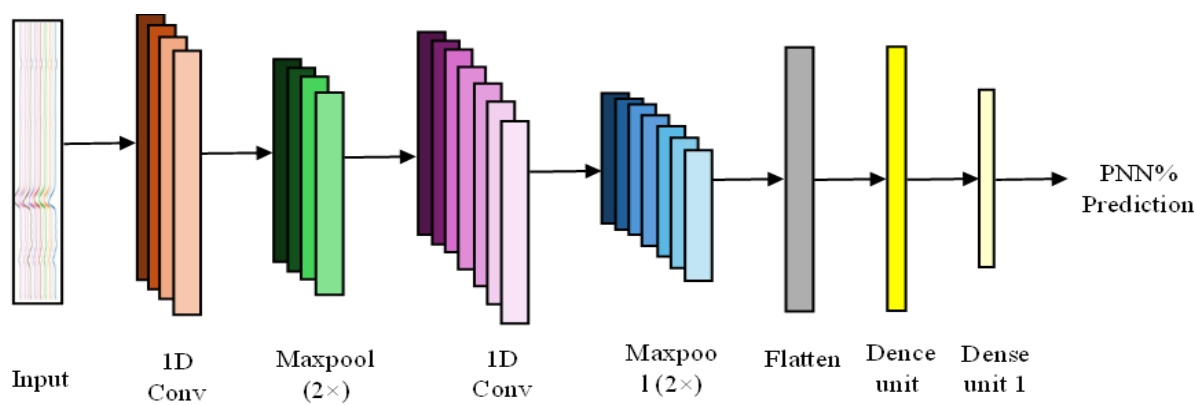


Figure 4.2. Architecture of the One-Dimensional Convolutional Neural Network (1D-CNN) used for petiole $\text{NO}_3\text{-N}$ (PNN) prediction. The model consists of sequential one-dimensional convolutional (1D conv) layers with Rectified Linear Unit (ReLU) activation functions, followed by max-pooling layers, flattening, and fully connected (dense) layers. The final output layer produces predicted PNN values.

4.3.6. Calibration transfer and model validation

Calibration transfer was performed using PDS to align field spectral datasets with spectra from fresh leaves measured in the lab. A sliding window of 11 wavelengths was used to compute transformation coefficients via the pseudo-inverse of the field spectral datasets matrix. Singular matrices were replaced with zero coefficients to maintain stability. The PDS technique harmonized spectral datasets across the 350–2500 nm range for predictive modelling.

Transformed field spectral datasets were filtered to include critical wavelengths identified by VIP analysis from the lab data. The performance of all three models (1D-CNN, SVR, and PLSR) was assessed using the R^2 , RMSE, and RPD to evaluate the effectiveness of calibration transfer.

4.4. Results

4.4.1. Preprocessed spectral patterns and key wavelengths for PNN prediction

The hyperspectral reflectance data obtained from field canopy, fresh leaf, and dried leaf samples were preprocessed using SG smoothing, SNV transformation, and FD calculation. This combination reduced noise and enhanced spectral features critical for PNN prediction. Figure 4.3 illustrates the preprocessed reflectance spectral datasets across treatments, showing consistent spectral patterns in the VNIR-SWIR regions.

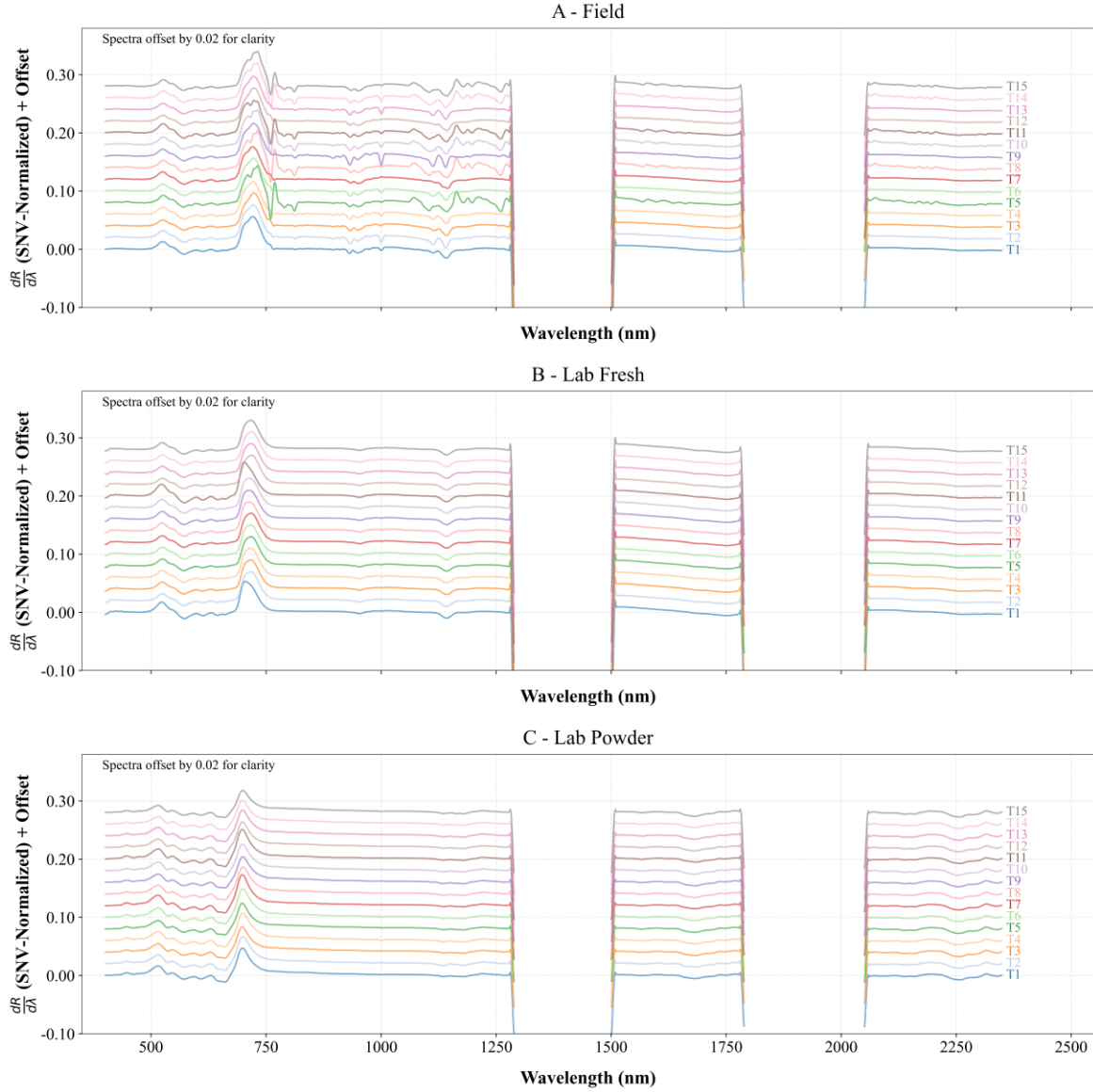


Figure 4.3. Preprocessed spectral reflectance (Savitzky-Golay smoothing, Standard Normal Variate transformation, and First Derivative transformation; SG-SNV-FD) of potato canopies across 15 treatments (T1–T15), measured over the 350–2500 nanometer (nm) wavelength range, with spectral datasets offset by 0.02 units for clarity. Panels A, B, and C depict spectral data collected under distinct conditions: field measurements, fresh leaf samples in the laboratory, and dried leaf samples in the laboratory, respectively.

VIP analysis based on PLSR was employed to identify the most influential wavelengths ($VIP \geq 1.5$) for predicting PNN across three spectral data sources. A total of 624, 661, and 530 bands were selected after VIP analysis from the field, laboratory fresh, and laboratory dried powder spectral

datasets, respectively. As shown in Figure 4.4, in the field canopy spectral dataset, most important wavelengths were found in the NIR (701–1100 nm) region, comprising 41.51% of the selected wavelengths, followed by the SWIR (1101–2500 nm) at 33.81% and the VIS range (400–700 nm) at 24.68%. Laboratory fresh leaf spectral dataset exhibited a more even distribution, with 40.85% of the important wavelengths in the VIS region, 39.94% in the SWIR, and 19.21% in the NIR. In contrast, the laboratory dried powder spectral dataset showed a strong emphasis on the SWIR region, accounting for 68.30% of the selected wavelengths, with substantially fewer wavelengths in the VIS (20.57%) and NIR (11.13%) regions.

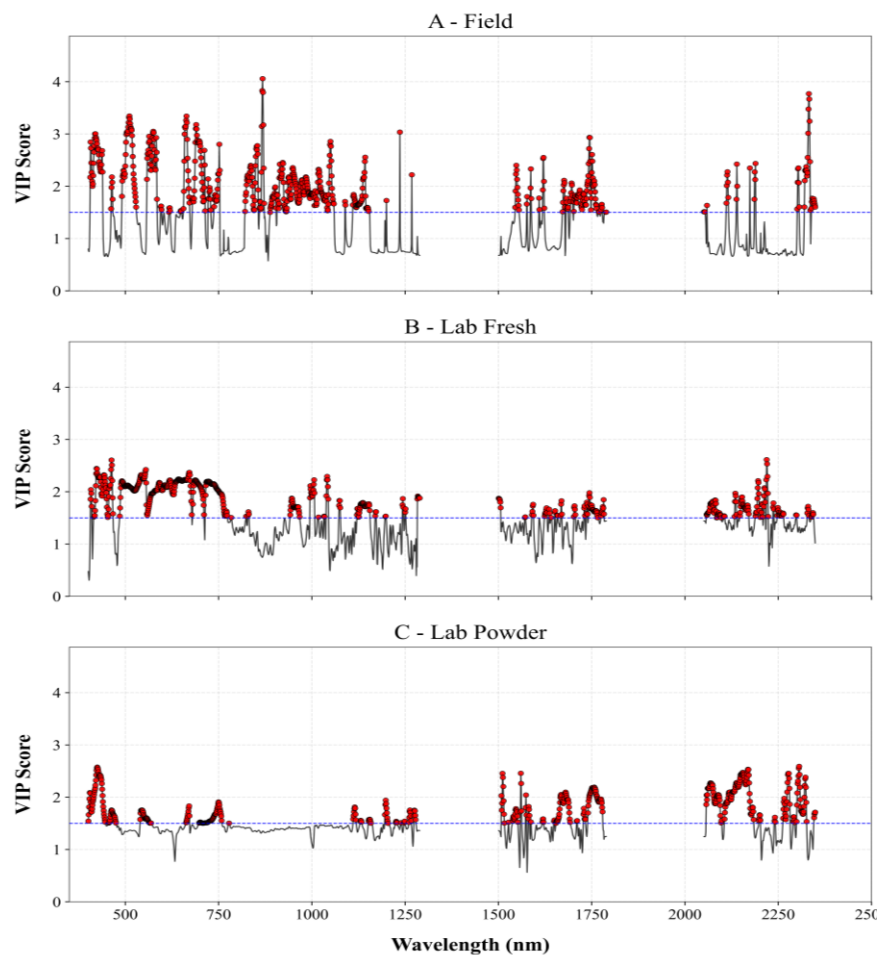


Figure 4.4. Variable Importance in Projection (VIP) scores for predicting petiole NO_3^- -N from preprocessed spectral datasets under three measurement conditions: (A) field canopy, (B) lab-fresh leaves, and (C) lab-dried powder. Red points indicate wavelengths with $\text{VIP} \geq 1.5$ used for model development, and the blue dashed line marks the $\text{VIP} = 1.5$ threshold.

4.4.2. Model performance across measurement conditions

The predictive accuracy of the 1D-CNN, SVR, and PLSR models, developed using spectral features with $\text{VIP} \geq 1.5$, varied across measurement conditions, as summarized in Figure 4.5.

Among the three measurement conditions evaluated with 1D-CNN, the laboratory fresh-leaf dataset produced the highest predictive accuracy ($R^2 = 0.90$, $\text{RMSE} = 0.22\%$, $\text{RPD} = 3.18$), followed by the laboratory dried-powder dataset ($R^2 = 0.81$, $\text{RMSE} = 0.28\%$, $\text{RPD} = 2.32$) and the

field canopy dataset ($R^2 = 0.77$, RMSE = 0.27%, RPD = 2.08). SVR showed moderate accuracy, with the laboratory fresh dataset yielding the best results ($R^2 = 0.60$, RMSE = 0.38%, RPD = 1.77), while the laboratory dried powder ($R^2 = 0.46$, RMSE = 0.45%, RPD = 1.49) and field models ($R^2 = 0.24$, RMSE = 0.55%, RPD = 1.19) exhibited greater variability. PLSR provided the weakest predictive performance among the three approaches, with the laboratory fresh condition achieving a moderate fit ($R^2 = 0.59$, RMSE = 0.39%, RPD = 1.74), and the field ($R^2 = 0.22$, RMSE = 0.55%, RPD = 1.18) and laboratory dried powder ($R^2 = 0.27$, RMSE = 0.53%, RPD = 1.22) models showing limited robustness.

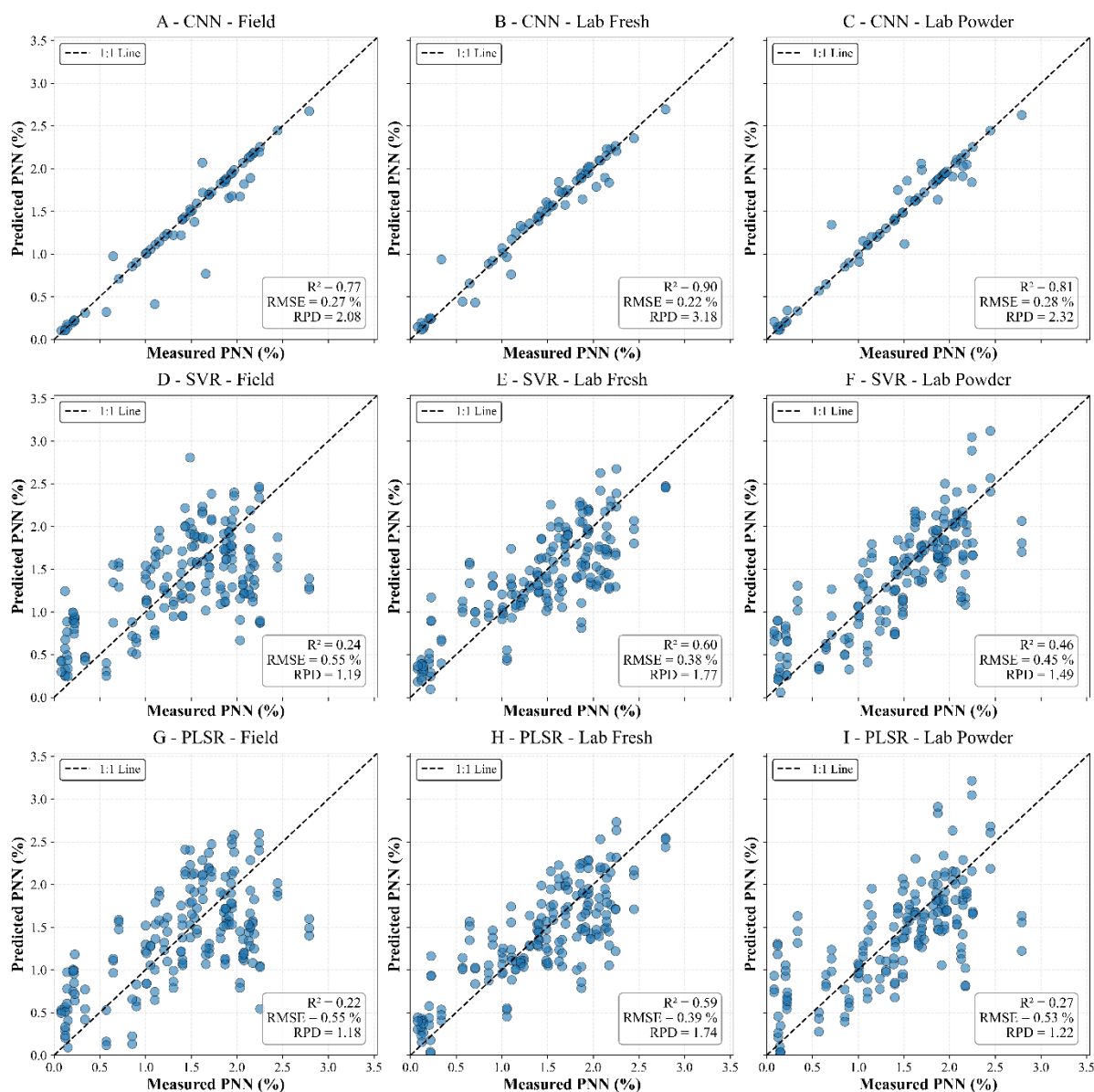


Figure 4.5. Scatter plots of predicted versus measured petiole NO_3^- -N (PNN) obtained from the models under three spectral measurement conditions: (A–C) One-Dimensional Convolutional Neural Network (1D-CNN), (D–F) Support Vector Regression (SVR), and (G–I) Partial Least Squares Regression (PLSR) using field, laboratory fresh, and laboratory dried powder datasets, respectively. Each plot reports the coefficient of determination (R^2), root mean square error (RMSE), and residual prediction deviation (RPD) calculated from the test dataset. The scatter points show predictions for the full dataset for visualization, whereas the reported values were calculated exclusively from the independent test subset.

4.4.3. Calibration transfer to enhance field-based PNN prediction

Applying PDS aligned the field spectral dataset more closely with the laboratory reference across the visible to near-infrared range. After calibration using PDS (Fig. 4.6), all models showed improved accuracy. The 1D-CNN showed the best performance ($R^2 = 0.82$, RMSE = 0.28%, RPD = 2.35), followed by SVR ($R^2 = 0.44$, RMSE = 0.47%, RPD = 1.40) and PLSR ($R^2 = 0.42$, RMSE = 0.48%, RPD = 1.38). Compared with models trained on uncalibrated field spectral dataset, the PDS-calibrated models achieved higher accuracy and more consistent predictions under field conditions. The reduced dispersion around the 1:1 line demonstrates that PDS effectively minimized the systematic deviation between field and lab spectral datasets.

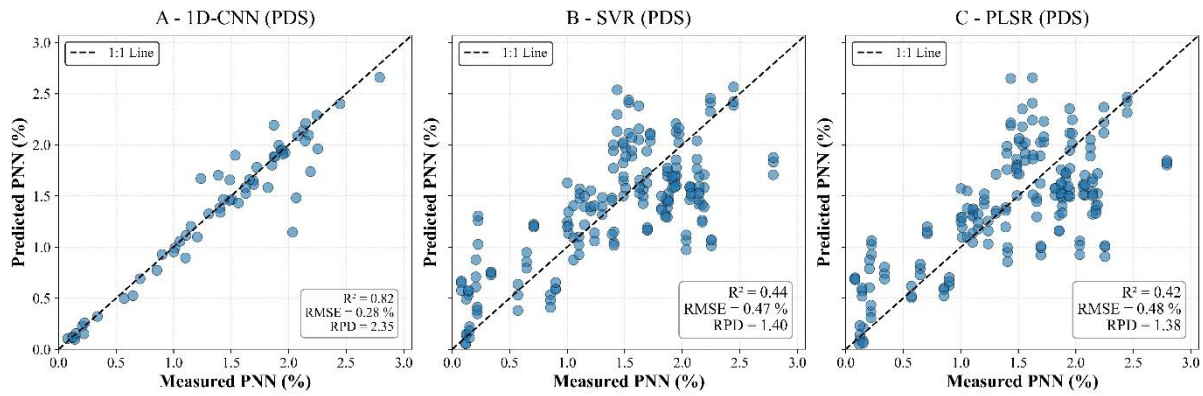


Figure 4.6. Predicted versus measured petiole NO_3^- -N (PNN) using One-Dimensional Convolutional Neural Network (1D-CNN), Support Vector Regression (SVR), and Partial Least Squares Regression (PLSR) models based on Piecewise Direct Standardization (PDS)-calibrated field spectral datasets. Each plot reports the coefficient of determination (R^2), root mean square error (RMSE), and residual prediction deviation (RPD) calculated from the test dataset.

4.5. Discussion

This study explored the potential of full-range VNIR-SWIR spectroscopy to predict in-season PNN in potato crops, addressing key objectives related to wavelength identification, predictive model development, measurement condition effects, and calibration transfer techniques. The

findings contribute to the understanding of hyperspectral reflectance for N management in potato systems, particularly in the Canadian Prairies, where such research is limited.

4.5.1. Identification of key wavelengths for PNN prediction

The selection of predictive wavelengths for PNN using VIP analysis underscored the strong influence of measurement conditions on spectral feature relevance. The identified spectral regions corresponded well with known chlorophyll absorption bands and molecular vibrations associated with N-containing compounds such as proteins and nucleic acids. L. Li et al. (2018) selected seven wavelengths (445, 556, 657, 764, 985, 1082, and 1194 nm) within the 400–1300 nm region; however, despite eliminating nearly 99 percent of the spectral variables, this reduced-band model achieved $r^2 = 0.85$, slightly lower than the full-spectrum result ($r^2 = 0.89$), indicating that model simplification did not improve predictive accuracy. In contrast, the present study retained a broader set of N-sensitive regions across the visible, near-infrared, and short-wave-infrared domains, capturing complementary biochemical information related to pigments, water, and proteins and improving prediction stability across different measurement conditions. Comparable wavelength-range selection strategies have been reported by Gill et al. (2024), who evaluated VIP distributions for winter wheat and highlighted key spectral regions with $VIP > 1$ that were most relevant to nutrient prediction, and by L. Fan et al. (2019), who combined multiple spectral variables across key absorption and reflection ranges to improve N estimation in corn. Collectively, these studies emphasize the importance of retaining physiologically meaningful wavelength regions to ensure accurate and stable N prediction without oversimplifying the spectral information.

4.5.2. Comparative performance of 1D-CNN, SVR, and PLSR models

Consistent with the present findings, several recent studies have demonstrated that convolutional and other deep learning architectures generally outperform traditional regression methods such as

SVR and PLSR in modelling N-related traits from spectral data (Valarezo-Plaza et al., 2024). These findings confirm that convolutional architectures can capture complex spectral–N relationships more effectively than kernel-based or linear approaches. For example, Carlier et al. (2023) reported that CNN models improved wheat N-related trait prediction compared with PLSR, particularly for N concentration, where the best ResNet50 model reached a validation R^2 of 0.80 compared with 0.54 for PLSR. In cotton, CNNR produced the lowest prediction error for leaf N concentration using full VNIR spectra, with root mean square error of prediction (RMSEP) = 3.36, compared with 3.42 for PLSR and 3.75 for SVR (Xiao et al., 2022). Likewise, for soil total N estimation, the hybrid CBiResNet-BiLSTM model achieved higher predictive performance than PLSR and SVR, with $R^2 = 0.937$, RMSE = 48.659 mg kg⁻¹, and RPD = 3.977, compared with $R^2 = 0.883$, RMSE = 66.272 mg kg⁻¹, and RPD = 2.920 for PLSR and $R^2 = 0.799$, RMSE = 86.661 mg kg⁻¹, and RPD = 2.151 for SVR (M. Sun et al., 2024). Such performance advantages highlight the potential of DL for operational nutrient-diagnostic applications in precision agriculture.

4.5.3. Predictive model performance across measurement conditions

The developed models for PNN prediction demonstrated varying performance across field canopy, laboratory fresh leaf, and laboratory dried leaf conditions. Contrary to the findings of Prananto et al. (2020), who reported that leaf powder samples yield better calibration performance due to standardized moisture content and particle size, our results indicate that fresh-leaf measurements provided higher predictive accuracy. This discrepancy may be attributed to the preservation of water-related absorption features in fresh leaves. Reflectance features linked to leaf water content, such as equivalent water thickness (EWT), can be influenced by leaf structural parameters, which in turn may be affected by N status (Ceccato et al., 2001). Supporting this, a marginal difference in N prediction performance was observed between fresh ($R^2 = 0.72$, RMSEP = 0.17) and dried

leaves ($R^2 = 0.71$, $RMSEP = 0.18$), suggesting that while drying helps standardize moisture, it may also obscure subtle N-related spectral signals (Kühn et al., 2024).

Field-based models exhibited the lowest performance, likely due to environmental factors such as variable solar illumination, leaf orientation, and complex canopy structure. These factors introduce significant variability in surface irradiance, making spectral signal interpretation more challenging (Pinto et al., 2016). This observation aligns with the findings of Prananto et al. (2020), who emphasized that laboratory conditions reduce external interferences, thereby improving the consistency and reliability of spectral measurements.

These results suggest that retaining natural moisture and pigment characteristics in fresh leaves enhances the spectral expression of N status compared with dried or canopy-level measurements.

4.5.4. Effectiveness of calibration transfer for field-based predictions

The application of PDS to align field spectral datasets with laboratory fresh leaf spectral datasets significantly improved the performance of the field-based models compared to raw field spectral datasets. This confirms the value of calibration transfer in reducing spectral variability caused by environmental and instrumental factors. For instance, applying PDS to NIR spectral data collected from different agricultural spectrometers reduced prediction errors in moisture and protein estimation, with RMSE decreasing from 0.159 to 0.116 for soybean meal moisture prediction (J. Yang et al., 2022). Similarly, applying an SVR-based calibration approach to fresh potato leaf spectral datasets substantially improved the estimation accuracy, reducing the RMSE from 0.069 to 0.026 and lowering the relative error in the SWIR region from 120% to 20% (Abukmeil et al., 2024). This demonstrates that calibration transfer can extend the utility of laboratory-calibrated models to real field conditions with improved stability and precision.

Despite the improvement achieved through PDS, the calibrated field models remained less accurate than the laboratory fresh leaf models. This remaining discrepancy likely reflects complex field-specific effects such as bidirectional reflectance, background interference, and leaf orientation, which are not fully corrected by transfer techniques.

4.5.5. Limitations and future directions

While this study highlights the strong potential of VNIR-SWIR spectroscopy for enhancing potato N management, several limitations should be acknowledged. The experiment was conducted at a single site and growth stage, which may restrict the general applicability of the developed models. Incorporating data from multiple locations, growing seasons, and developmental stages would help account for environmental variability and improve model robustness, as shown by S. Wang et al. (2021) in maize. In addition, future work should explore integrating field spectroscopy with unmanned aerial vehicle (UAV) or satellite imagery to develop scalable N-monitoring frameworks.

4.6. Conclusion

This study demonstrated the effectiveness of VNIR-SWIR spectroscopy combined with 1D-CNN, SVR, and PLSR models for estimating PNN in potato crops under both field and laboratory measurement conditions. Spectral regions within the VIS and SWIR bands were identified as critical for N prediction, aligning with known absorption features related to chlorophyll and N-containing compounds. Among the three measurement approaches, fresh leaf spectral datasets acquired under controlled laboratory conditions yielded the most accurate predictions, suggesting the importance of minimizing external variability during spectral acquisition. The 1D-CNN used in this study was a simple yet efficient architecture for predicting N content in potato crops, effectively capturing spectral–N relationships across different measurement conditions. Field-

based predictions showed lower accuracy, but calibration transfer via PDS improved model performance by reducing spectral discrepancies between environments. These findings emphasize the need for standardized spectral measurement protocols and effective calibration transfer methods to ensure reliable N prediction under diverse measurement conditions, which could ultimately support optimised fertilizer management, reduced input costs, and more sustainable potato production.

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Chapter 5

**Joint Prediction of Potato Yield and Nitrogen
Status at Row Closure Using Multi-Task Deep
Learning and UAV-Derived LiDAR–
Multispectral Data**

5.1. Abstract

Accurate prediction of crop yield and nitrogen (N) status from remote sensing data remains challenging due to fundamental differences in how cumulative and physiological traits are expressed at the canopy level. This study investigated a multi-task learning (MT) framework based on deep learning (DL) for the joint prediction of potato tuber yield and petiole NO_3^- -N (PNN) using fused unmanned aerial vehicle (UAV)-derived multispectral (MS) and LiDAR data acquired at row closure across two growing seasons. Model performance was evaluated against single-task learning (ST) across multiple network architectures using independent test data. Joint optimisation substantially improved yield prediction relative to yield-only models, increasing test R^2 from ≤ 0.26 under ST to 0.46–0.60 across MT architectures, whereas benefits for PNN were limited and architecture dependent. Attribution analysis indicated that yield prediction relied on a broader combination of spectral and three-dimensional canopy features, with LiDAR-derived height, volumetric, and heterogeneity metrics contributing consistently but with lower relative importance than spectral indices. In contrast, PNN prediction was dominated by chlorophyll-sensitive spectral indices, consistent with its short-term physiological basis. These results show that shared-learning frameworks in potato systems are most useful when the sensing inputs and model structure are matched to the physiological timescale of the target trait.

5.2. Introduction

Potato (*Solanum tuberosum* L.) is one of the most widely cultivated food crops globally and plays an important role in food security due to its high yield potential, nutritional value, and adaptability across diverse agro-climatic regions (Devaux et al., 2014). Global potato production has expanded steadily in recent decades, driven by increasing demand for processed products and by the crop's

capacity to deliver high caloric output per unit area (Caliskan et al., 2022). In Canada, potato production reached approximately 6.5 million tonnes in 2023, with average yields of 41.8 t ha⁻¹, which is nearly twice the global mean of 22.8 t ha⁻¹ (FAOSTAT, 2023). Nearly half of this production is concentrated in the Prairie provinces, where Manitoba and Alberta consistently rank among the highest-yielding regions (Statistics Canada, 2025). Sustaining this level of productivity while minimizing environmental impacts remains a central challenge for Canadian potato production systems.

Nitrogen (N) fertilization is a dominant driver of potato yield and tuber quality, yet it is also a major source of environmental concern (Vos, 2009). Potato crops typically exhibit low N use efficiency (NUE), often below 50–60%, resulting in substantial losses through nitrate leaching and gaseous emissions (Goffart et al., 2023). In irrigated Prairie soils, which are frequently coarse-textured and prone to rapid drainage, excessive or poorly timed N applications can lead to elevated nitrate leaching and increased N₂O emissions (X. Gao et al., 2018; Yadav & Wang, 2021). These risks are exacerbated by strong within-field variability in crop N demand and by climate-driven fluctuations in soil moisture that influence N availability and uptake dynamics (Allaire et al., 2014; H. Liu et al., 2022). Consequently, uniform fertilizer application strategies are increasingly inefficient, underscoring the need for spatially explicit monitoring approaches capable of supporting precision N management.

N availability directly influences potato canopy development by regulating vegetative growth, leaf expansion, and chlorophyll synthesis. Adequate N supply promotes greater canopy height, stem thickness, and above-ground biomass accumulation, whereas N deficiency leads to reduced leaf area, shortened petioles, thinner stems, and suppressed canopy structure (Muharam et al., 2014; Tehulie & Misgan, 2019). These structural responses are closely linked to tuber growth, as above-

ground biomass and canopy architecture govern light interception, assimilate production, and partitioning to developing tubers. Field studies have consistently demonstrated strong relationships between above-ground biomass accumulation and final tuber yield, highlighting canopy structure as an integrative indicator of yield potential in potato systems (Chen et al., 2025; B. Li et al., 2020b).

Remote sensing (RS) technologies provide a practical means of monitoring crop canopy status non-destructively and at high spatial resolution. Multispectral (MS) sensing has been widely adopted to assess crop N status through vegetation indices (VIs) sensitive to leaf chlorophyll concentration and photosynthetic activity (Çimtay, 2023; Santos et al., 2025). These indices have demonstrated strong capability for capturing spatial variability in crop nutritional status, particularly during early to mid-season growth stages. However, VIs derived from MS data are known to exhibit reduced sensitivity and saturation under dense canopy conditions and high leaf area index, limiting their utility for additional biomass and structural variation (S. Gao et al., 2023; Yan et al., 2025). In addition, spectral measurements provide limited direct information on canopy three-dimensional architecture, which is important in light interception, biomass allocation, and yield formation.

Light detection and ranging (LiDAR) is an active RS technology that measures distances using laser pulses to generate high-precision three-dimensional representations of surface features. Since its early development in the mid-twentieth century (Irish & Lillycrop, 1999), advances in sensor miniaturisation, global navigation satellite system (GNSS) positioning, inertial measurement unit (IMU) integration, and multi-return laser systems have enabled widespread adoption of LiDAR across terrestrial and agricultural applications. Recent progress in unmanned aerial vehicle (UAV)-mounted LiDAR platforms has made it possible to acquire dense point clouds at the plot and field

scales, facilitating detailed characterization of crop canopy structure, including height distribution, volumetric development, and vertical heterogeneity (Rivera et al., 2023). Numerous studies have demonstrated that LiDAR-derived structural metrics capture aspects of crop growth and biomass that are not fully represented by spectral data alone, thereby improving the estimation of yield-related traits (Farhan et al., 2024; Maimaitijiang et al., 2020).

Parallel to advances in sensing technologies, deep learning (DL) methods have emerged as powerful tools for extracting complex, non-linear relationships from high-dimensional agricultural data. Deep neural architectures are capable of learning latent feature representations that integrate spectral and structural information, enabling improved prediction of crop traits such as yield and N status (Sarker, 2021). DL has been successfully applied to yield prediction in multiple cropping systems, including rice and cotton, using UAV-based RS data (A. Feng et al., 2024; H. Zhou et al., 2025). Similarly, DL frameworks have shown strong potential for estimating N-related traits using hyperspectral and multi-modal RS data (Nguyen et al., 2023; Y. Peng et al., 2024). Despite these advances, applications in potato production remain comparatively limited, particularly those integrating UAV-derived LiDAR structural metrics with MS information within unified DL frameworks.

The review presented in Chapter 2 emphasized the growing potential of integrating advanced sensing technologies with machine learning to support site-specific nutrient management in Canadian potato systems, while also highlighting the limited number of studies conducted in Prairie production systems and the need for more comprehensive multi-sensor investigations. Although both spectral and structural canopy information are increasingly available from UAV platforms, their combined use within unified learning frameworks remains limited, particularly for jointly characterizing N status and yield formation. Recent work has demonstrated that multi-task

learning (MT) frameworks can improve yield prediction stability by sharing information across related prediction tasks, while also requiring careful loss balancing to prevent dominance of individual tasks and uneven generalization across outputs (H. Wang et al., 2025). By jointly modelling yield and N from the same canopy observations, MT offers a mechanism to exploit shared physiological and structural information that is not captured when these traits are modelled independently using single-task (ST) frameworks. Addressing these gaps is essential for developing robust decision-support tools capable of improving N use efficiency while maintaining high yield productivity in Canadian potato systems.

Unlike many previous UAV-based crop monitoring studies that rely on multi-temporal imagery for yield assessment or model target traits separately, including yield or crop N status (e.g., Ashapure et al., 2020; Ding et al., 2022; Fei et al., 2023), this work uses multi-task learning as a controlled framework to test whether two agronomically related but physiologically distinct potato traits—final tuber yield and in-season petiole nitrate-N—can benefit from a shared canopy representation. The analysis focuses on a single row-closure acquisition, where LiDAR-derived structural metrics and multispectral vegetation indices were combined to represent canopy architecture and spectral N response. By comparing multi-task and single-task models under identical input features, data partitions, preprocessing steps, and network architectures, the effect of shared learning is separated from other modelling choices. This design extends existing RS-based crop monitoring approaches by evaluating not only whether joint learning improves prediction, but also when it introduces task-specific trade-offs and how spectral and structural features contribute differently to cumulative yield and short-term physiological N status.

The objectives of this study were to: (i) quantify the predictive value of fused UAV-derived LiDAR canopy structural metrics and MS features for estimating potato tuber yield and petiole nitrate-N

(PNN, %) at the plot scale; (ii) evaluate whether shared representation learning under MT improves, constrains, or redistributes predictive performance for yield and PNN relative to ST models trained under identical features, data partitions, preprocessing steps, and network architectures; and (iii) identify and rank the dominant spectral and structural drivers of each prediction task using post-hoc attribution analysis, thereby distinguishing shared versus task-specific feature dependence.

5.3. Materials and methods

To ensure comparability across learning paradigms and network architectures, all analyses were conducted within a unified workflow encompassing data acquisition, feature derivation, model training, and evaluation. An overview of the multi-sensor data acquisition and modelling workflow is presented in Fig. 5.1.

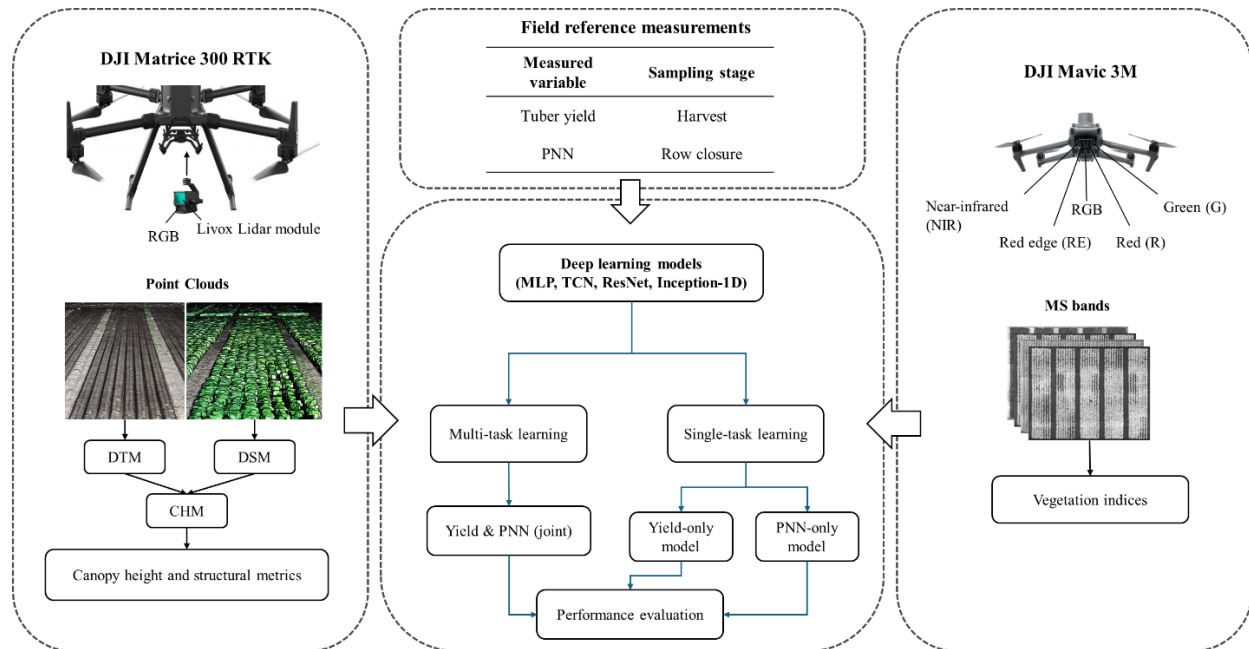


Figure 5.1. Overview of the integrated workflow for multi-sensor data acquisition, feature derivation, and deep learning (DL)-based modelling. Airborne LiDAR data were used to generate point clouds and derive canopy height and structural metrics, including the Digital Terrain Model (DTM), Digital Surface Model (DSM), and Canopy Height Model (CHM). Multispectral (MS) imagery was used to compute VIs from

near-infrared, red-edge, red, green, and RGB bands. Field measurements provided reference observations for tuber yield and petiole NO_3^- -N (PNN). These inputs were used to train DL models, including Multilayer Perceptron (MLP), Temporal Convolutional Network (TCN), Residual Network (ResNet), and one-dimensional Inception network (Inception-1D), under both multi-task and single-task learning frameworks, followed by model performance evaluation.

5.3.1. Experimental design and field sampling

Field experiments were conducted during the 2024 and 2025 growing seasons in two adjacent irrigated potato research fields near Carberry, Manitoba, Canada (Fig. 5.2). The 2024 site was located at 49.931646° N, 99.391122° W, and the 2025 site at 49.932642° N, 99.393776° W. Both sites are situated within the primary irrigated potato production region of southwestern Manitoba, which is characterized by coarse-textured soils with rapid drainage and strong crop responsiveness to N availability. Baseline soil characterization showed soil organic matter averaging 1.9%, soluble salt concentrations ≤ 0.15 mmho cm^{-1} , soil pH ranging from 5.3 to 5.6, and cation exchange capacity of approximately 30.3 meq 100 g^{-1} , indicating non-saline, acidic soil conditions typical of irrigated potato systems in southwestern Manitoba. The cultivar *Russet Burbank* was grown in both seasons because it is the dominant processing cultivar in Canada and exhibits well-established sensitivity to N supply, making it suitable for evaluating treatment-induced variation in canopy development and plant N status (Carew et al., 2009).

Despite independent seasonal management, experimental design and measurement protocols were kept consistent across years. In 2024, the experiment consisted of 60 plots arranged as 15 N treatments with four replicates. In 2025, the design was expanded to 112 plots comprising 28 treatments, also replicated four times. Individual experimental units measured approximately 12.8 $\times$ 3.7 m. The fertilizer program included ammonium sulfate, urea, enhanced-efficiency fertilizers (ESN and SuperU), and fertigation, applied across a structured N rate range from 0 to 224 kg ha^{-1}

to establish a broad and controlled gradient of N availability. All plots were managed following standard commercial practices for irrigated potato production in Manitoba, including uniform tillage, irrigation, and pest management.

Because fertilizer source, timing, and rate jointly influence plant N availability, treatment effects were evaluated using PNN at row closure as a direct, plant-based indicator of crop N status rather than nominal fertilizer application rates. Petiole sampling was conducted at the row-closure growth stage, occurring at approximately 60 days after planting (DAP) under the growing conditions of this study, when differences in canopy height, biomass accumulation, and canopy structural development are most pronounced under contrasting N supply. For each plot, the fourth petiole from the apex of representative plants was selected, leaflets were removed, and approximately thirty petioles were composited to obtain a representative sample of within-plot variability. Samples were labeled immediately after collection and analysed for nitrate-N concentration by a commercial laboratory (Agvise Laboratories, USA) using standardised analytical procedures. Laboratory-reported nitrate-N values were subsequently expressed as percentage (%) for consistency across analyses.

The two adjacent fields shared comparable soil characteristics but differed slightly in local spatial variability and historical management, enabling independent evaluation of N response patterns under otherwise consistent agronomic operations. Tuber yield was determined at physiological maturity using plot-scale harvests, with all marketable tubers from each experimental unit harvested and weighed. Yield was expressed on an area basis as fresh tuber yield (t ha^{-1}), and measurements were conducted consistently across both seasons to ensure comparability between years and treatments.

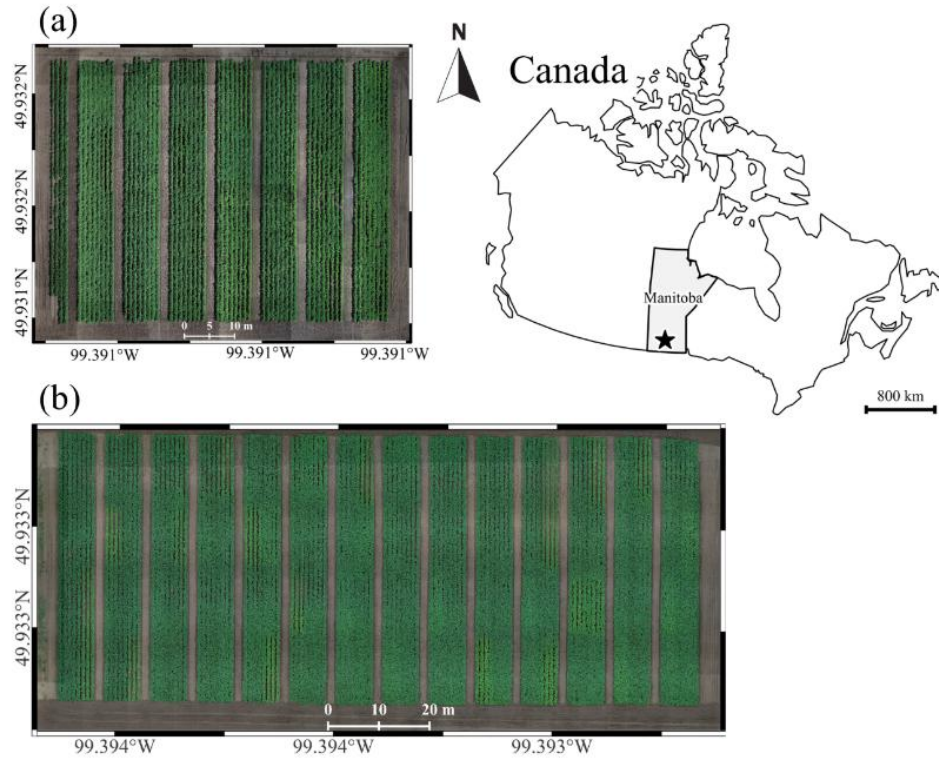


Figure 5.2. Location and layout of the experimental potato fields near Carberry, Manitoba, Canada. The inset map indicates the position of the study area within Canada. Panels (a) and (b) show the experimental fields used during the 2024 and 2025 growing seasons, respectively, based on orthomosaic imagery.

5.3.2. Multispectral and LiDAR data collection

UAV-based MS and LiDAR data were acquired using coordinated flight campaigns designed to ensure spatial and temporal alignment between sensors and field measurements. All UAV flights were conducted at a consistent altitude of 15 m above ground level, and MS and LiDAR acquisitions were performed on the same day and aligned with concurrent petiole sampling at the row-closure growth stage. In addition, LiDAR data were collected over bare-soil conditions immediately following hilling operations, prior to canopy development, to support accurate ground surface characterization.

MS imagery was collected using a DJI Mavic 3 Multispectral (Mavic 3M) UAV equipped with an integrated MS imaging system. The sensor suite consists of four MS cameras (5 MP each) capturing reflectance data in the green (560 ± 16 nm), red (650 ± 16 nm), red-edge (730 ± 16 nm), and near-infrared (860 ± 26 nm) spectral bands. In addition, the platform includes a 20 MP RGB camera with a 4/3-inch CMOS sensor and a mechanical shutter, which was used for high-resolution true-colour imagery when required. Flights were executed using automated mission planning with parallel flight lines to ensure uniform spatial coverage of the experimental plots. A consistent flight speed was maintained, with forward and lateral overlaps set to 80% and 70%, respectively, to minimise geometric distortion and ensure robust image alignment. MS data acquisition was conducted under stable illumination conditions to reduce the effects of variable solar angle and cloud cover.

LiDAR data were acquired using a DJI Matrice 300 RTK UAV equipped with a Zenmuse L1 LiDAR payload mounted on a three-axis stabilised gimbal. The Matrice 300 RTK is an industrial multirotor platform designed for survey applications, providing high flight stability and endurance for consistent data acquisition over agricultural plots. The Zenmuse L1 integrates a Livox solid-state LiDAR sensor operating at 905 nm, a high-accuracy inertial measurement unit (IMU), and an RGB camera with a 1-inch CMOS sensor. The LiDAR system employs a non-repetitive scanning pattern, supports up to three discrete returns per pulse, and provides an effective sampling rate of up to 240,000 points s^{-1} with a circular field of view of 70.4° , enabling dense spatial sampling and accurate representation of crop canopy structure. LiDAR flights were conducted along parallel flight lines to ensure uniform point distribution across the study area. In addition to row-closure acquisitions, LiDAR data collected under bare-soil conditions following hilling

operations were used for ground surface modelling and subsequent derivation of canopy structural metrics.

Both UAV platforms are equipped with onboard real-time kinematic (RTK)-enabled global navigation satellite system (GNSS) rovers. For all UAV flights, RTK corrections were provided using a DJI D-RTK 2 Mobile Station deployed within the study area. The D-RTK 2 functioned as a local base station, supplying continuous correction data under fixed RTK conditions and ensuring consistent, centimetre-level geotagging and georeferencing across MS and LiDAR datasets.

The coordinated timing, consistent flight parameters, and shared RTK correction source ensured accurate spatial alignment between MS imagery, LiDAR-derived structural metrics, and ground-based measurements.

5.3.3. Data preprocessing and post-processing

Multispectral imagery was processed using DJI Terra (version 5.1.1) to generate georeferenced MS orthomosaics. Standard photogrammetric procedures, including image alignment and mosaicking, were applied to ensure consistent geometric reconstruction across acquisitions. Radiometric calibration and normalization were performed using the manufacturer-recommended processing workflow, incorporating data from an onboard sunlight sensor to account for variations in ambient illumination during data acquisition. No external reflectance calibration panels were used, and MS values therefore represent relative surface reflectance suitable for vegetation index computation.

VIs were calculated in QGIS (version 3.44) to characterize canopy spectral responses related to vegetation vigour and chlorophyll activity. The selected indices have been reported to exhibit strong relationships with potato N status and, in some cases, tuber yield when derived from MS

imagery, as shown in Chapter 3 and in related studies (Canicatti et al., 2025; Javed et al., 2025). All indices were computed on a per-pixel basis, and plot-level mean values were subsequently extracted using polygon-based zonal statistics to ensure direct correspondence with LiDAR-derived structural metrics. The VIs and their formulations are summarized in Table 1.

Initial processing of LiDAR data, including GNSS–IMU trajectory refinement and strip alignment, was performed using DJI Terra. The resulting georeferenced point clouds were exported in LAS format for subsequent analysis. Further point-cloud processing and surface model generation were conducted using CloudCompare (version 2.14.beta).

DTM and DSM layers were generated from the LAS point clouds using standard ground-filtering and rasterization procedures. CHMs were derived by subtracting the DTM from the DSM. Negative CHM values were set to zero to eliminate artefacts arising from residual interpolation errors and to ensure physically meaningful canopy height estimates. LiDAR-derived raster products, including DTM, DSM, and CHM, were generated at a spatial resolution of 0.5 m. The resulting MS orthomosaics had a ground sampling distance of approximately 0.5 cm, as determined from the reconstructed orthomosaic metadata. Plot-level features were subsequently extracted using zonal statistics, ensuring that differences in native raster resolution did not affect the comparability of plot-aggregated spectral and structural metrics.

Canopy structural information was extracted from the CHMs using zonal statistics at the plot level. A canopy mask was generated to distinguish vegetation from background based on a height threshold, whereby pixels exceeding 0.25 m were classified as canopy. Canopy cover was calculated as the percentage (%) of canopy-classified pixels within each plot relative to the total plot area and was subsequently used in the derivation of composite structural metrics. Upper-canopy development was characterized using CHM_p95, which provides a robust representation

of dominant canopy structure while reducing sensitivity to local outliers and within-canopy variability. All canopy height-based structural metrics were computed using CHM values extracted exclusively from canopy-classified pixels within each plot. Non-canopy pixels were excluded prior to calculation to avoid biasing height distributions and variability metrics.

Based on this structural representation, additional volumetric, uniformity, and biomass-related descriptors were derived to characterize canopy spatial development and structural heterogeneity. Definitions and formulations of all LiDAR-derived structural metrics are provided in Table 5.1. Similar LiDAR-derived canopy height statistics, height variability measures, and canopy volume-based structural descriptors have been widely used to characterize vegetation structure and biomass-related attributes in airborne LiDAR studies (de Almeida et al., 2019; Z. Zhang et al., 2017).

Table 5.1. Spectral vegetation indices and LiDAR-derived structural metrics used in this study, including definitions and formulations.

	Index	Long name	Equation	Reference
Spectral	NDVI	Normalized Difference Vegetation Index	$NDVI = \frac{NIR - Red}{NIR + Red}$	(Rouse et al., 1974)
	GNDVI	Green Normalized Difference Vegetation Index	$GNDVI = \frac{NIR - Green}{NIR + Green}$	(A. Gitelson & Merzlyak, 1994)
	Cl_green	Green chlorophyll index	$Cl_{green} = \frac{NIR}{Green} - 1$	(A. A. Gitelson et al., 2003)
Structural	CHM_p95 (m)	95th percentile canopy height	$CHM_{p95} = \text{quantile}_{0.95}(CHM)$	(Popescu et al., 2002)
	CV (m ³)	Canopy volume	$CV = CHM_{sum} \times (\text{pixel size})^2$	-
	CSI	Canopy structure index	$CSI = (\frac{\text{canopy cover}}{100}) \times CHM_{p95}$	-
	CH _{ratio}		$CH_{ratio} = \frac{CHM_{mean}}{CHM_{max}}$	-
	BP (m ²)	Biomass proxy	$BP = (\frac{\text{canopy cover}}{100}) \times CHM_{mean} \times CHM_{p95}$	-
	H _{cv}	Height coefficient of variation	$H_{cv} = \frac{CHM_{stdev}}{CHM_{mean}}$	-

5.3.4. Deep learning framework for nitrogen and yield prediction

The DL framework was designed to enable a controlled comparison of ST and MT for tuber yield and PNN prediction using identical sensor-derived inputs acquired at row closure. By fixing data partitioning, preprocessing, and training procedures across all models, the framework isolates the influence of learning paradigm and network architecture on predictive performance.

5.3.4.1 Experimental design and learning scenarios

DL models were implemented using two learning paradigms, ST and MT, to predict tuber yield and PNN within a unified modelling framework. In the ST paradigm, separate models were trained independently for yield and PNN, whereas in the MT paradigm a shared feature representation was learned jointly for both targets, followed by task-specific output heads, consistent with established MT formulations in agricultural modelling (Fang et al., 2024).

All experiments were conducted within a unified modelling framework, using identical data splits, preprocessing steps, and training protocols to ensure direct comparability across architectures and learning strategies. Models were trained on pooled data from the 2024 and 2025 growing seasons using identical input features, train–validation–test splits, and preprocessing pipelines. This controlled design isolates the effects of network architecture and learning strategy from confounding influences related to data partitioning or feature scaling, following established practices for fair comparison of DL models in agricultural prediction tasks.

A total of twelve DL models were trained, comprising four neural network architectures evaluated under three learning scenarios: MT (joint prediction of yield and PNN), ST yield prediction, and ST PNN prediction.

5.3.4.2 Input features and data partitioning

Model inputs consisted exclusively of sensor-derived features, including MS VIs and LiDAR-based canopy structural metrics. Identifiers such as plot ID and year were excluded from the input feature set to prevent target leakage and ensure that predictions relied solely on biophysically meaningful information.

The dataset was partitioned into training, validation, and test subsets using a stratified procedure based on year, ensuring balanced representation of the 2024 and 2025 seasons across all subsets. The final split comprised approximately 70% training, 15% validation, and 15% testing samples. Missing feature values were imputed using the median of the training set only, and all input features were standardized using z-score normalization derived from training data. Target variables were standardized separately during model training and subsequently transformed back to their original units for evaluation and reporting.

5.3.4.3 Network architectures

The four architectures were selected to compare distinct ways of learning feature interactions from the same fused MS–LiDAR input space while keeping the model comparison focused and interpretable. The MLP was used as a fully connected tabular baseline because it does not impose local structure on the input features. The TCN and Inception-1D models were included as one-dimensional convolutional backbones to test whether local and multi-scale interactions across an ordered sensor-feature vector could improve representation learning; this choice was informed by prior work showing that convolutional architectures with dilated receptive fields can provide effective representations for ordered inputs (Bai et al., 2018), and that Inception-style one-dimensional architectures can extract features across multiple filter lengths (Fawaz et al., 2020). ResNet was included to evaluate whether residual connections could support deeper transformations of the fused feature space while reducing degradation during training, following the residual-learning principle introduced by He et al., (2016). This architecture set therefore allowed the comparison of fully connected, dilated convolutional, residual, and multi-scale convolutional representations under identical inputs, data partitions, and training procedures.

For MT models, a shared backbone network with common weights was used to extract latent feature representations from the full input feature set, followed by two task-specific output heads corresponding to yield and PNN prediction. ST models employed identical backbone architectures but retained only a single output head associated with the target variable.

Across all architectures, dropout regularization (dropout rate = 0.15) and batch normalization were applied to improve generalization. The evaluated architectures included MLPs with three hidden layers (256–128–64 units), TCNs with dilated convolutional blocks (channels = 32–64–64), ResNet models composed of four stacked residual blocks (latent dimension = 256), and Inception-1D models combining parallel convolutional kernels of sizes 3, 5, and 7.

5.3.4.4 Model training and optimisation

All DL models were trained using the AdamW optimiser (learning rate = 2×10^{-3} , weight decay = 1×10^{-4}), with weight decay applied as a regularisation term. The learning rate was adaptively adjusted using a ReduceLROnPlateau scheduler based on validation loss. Training was conducted for up to 300–400 epochs, depending on architecture, with early stopping applied when validation loss failed to improve for 35 consecutive epochs, at which point the model state corresponding to the minimum validation loss was retained.

For the main MT comparison, the training objective was defined as the sum of standardized mean squared errors for yield and PNN, providing an equal-weight baseline for evaluating shared learning under matched modelling conditions. To assess whether model behaviour was sensitive to fixed task weighting, an additional MT loss-weight sensitivity analysis was conducted using:

$$L_{MT} = \alpha \text{MSE}_{\text{Yield}} + (1 - \alpha) \text{MSE}_{\text{PNN}}$$

where α represents the relative weight assigned to the yield loss. The tested values were $\alpha = 0.3$, 0.5, and 0.7. All sensitivity runs used the same input features, data partitions, preprocessing steps, architecture settings, and training procedure as the main MT models.

Model performance was evaluated on training/validation and independent test datasets using complementary metrics, including the coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and residual prediction deviation (RPD), computed in the original units of yield (t ha^{-1}) and PNN (%). Parity plots and residual diagnostics were used to examine predictive accuracy, bias, and error structure across models, with identical axis limits and styling applied to ensure consistent visual comparison across architectures.

5.3.4.5 Attribution analysis framework

GradientShap attribution analysis was applied to MT models to interpret model predictions by quantifying the marginal contribution of each input feature to the predicted yield and PNN outputs. This enables identification of the spectral and structural variables that the trained networks rely on most strongly, providing insight into how canopy reflectance and LiDAR-derived structural information are combined to generate predictions. Such attribution analysis facilitates assessment of whether learned feature dependencies are agronomically consistent and physically interpretable, as demonstrated in recent applications of explainable deep learning for crop yield forecasting (Paudel et al., 2023).

Attributions were computed using up to 200 randomly sampled training instances as baselines (limited by the available training sample size), and attribution inputs consisted of all available independent test samples ($n = 26$ in this study). GradientShap attributions were estimated using 60 stochastic samples per input with a Gaussian noise standard deviation of 0.09. Mean absolute

GradientShap values were aggregated across inputs to derive global feature-importance rankings, while beeswarm plots were used to examine the distribution and directionality of feature effects.

5.4. Results

5.4.1. Single-task prediction performance

ST models exhibited contrasting predictive performance for tuber yield and PNN. Yield prediction under the ST framework was limited, with test-set R^2 ranging from 0.02 to 0.26 across architectures and corresponding RMSE values between 4.23 and 4.86 t ha⁻¹ (Table 5.2).

In contrast, ST prediction of PNN achieved substantially higher accuracy and stability. Test-set R^2 values reached up to 0.71, with RMSE values as low as 0.24%, depending on architecture (Table 5.2). Among the evaluated models, ST-TCN achieved the highest test-set performance for PNN, followed by ST-ResNet. Parity plots showed tight clustering of observations around the 1:1 line across the full concentration range, with no pronounced systematic bias (Fig. 5.3). These results indicate that PNN was more reliably predicted than yield under ST, reflecting stronger and more direct relationships between canopy features and crop N status.

Table 5.2. Performance of single-task (ST) deep learning models for predicting potato tuber yield (t ha^{-1}) and petiole NO_3^- -N (PNN, %) using UAV-derived multispectral and LiDAR features. Model accuracy is reported for the combined training/validation dataset ($n = 146$) and an independent test dataset ($n = 26$) using the coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and ratio of performance to deviation (RPD).

Model	Variable	Dataset	R^2	RMSE	MAE	RPD
ST-MLP	Yield	Train/Val	0.19	3.98	3.19	1.12
		Test	0.26	4.23	3.29	1.19
	PNN	Train/Val	0.72	0.30	0.22	1.90
		Test	0.59	0.29	0.22	1.59
ST-TCN	Yield	Train/Val	0.14	4.10	3.25	1.09
		Test	0.15	4.54	3.42	1.11
	PNN	Train/Val	0.80	0.25	0.20	2.26
		Test	0.71	0.24	0.19	1.89
ST-ResNet	Yield	Train/Val	0.16	4.07	3.27	1.09
		Test	0.21	4.37	3.36	1.15
	PNN	Train/Val	0.87	0.21	0.15	2.79
		Test	0.56	0.30	0.21	1.54
ST-Inception	Yield	Train/Val	0.03	4.36	3.44	1.02
		Test	0.02	4.86	3.60	1.03
	PNN	Train/Val	0.74	0.29	0.22	1.98
		Test	0.57	0.30	0.25	1.56

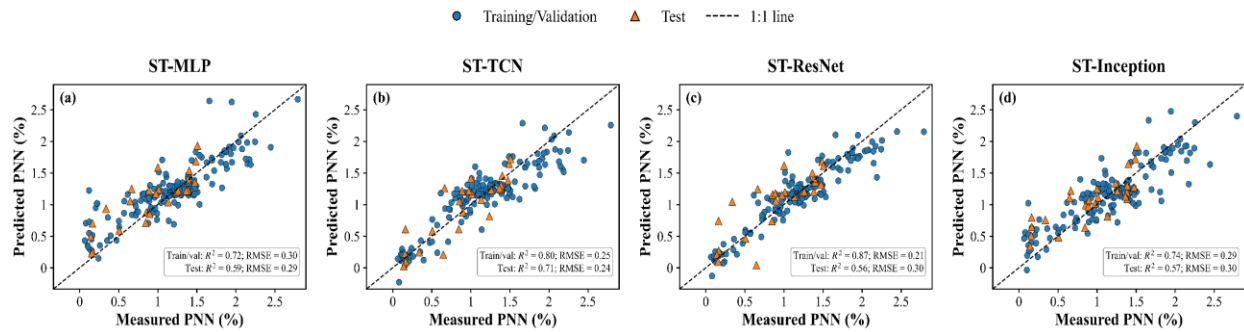


Figure 5.3. Parity plots comparing measured and predicted PNN (%) for single-task (ST) deep learning models, including ST-MLP (a), ST-TCN (b), ST-ResNet (c), and ST-Inception (d). Blue circles represent combined training/validation samples, and orange triangles represent independent test samples. The dashed line denotes the 1:1 relationship. Model performance statistics (R^2 and RMSE) are reported separately for the training/validation and independent test datasets within each panel.

5.4.2. Joint learning behaviour of yield and nitrogen under multi-task optimisation

MT substantially improved tuber yield prediction relative to ST baselines. Across all architectures, test-set yield R^2 increased to 0.46–0.60, accompanied by reduced RMSE values of 3.13–3.63 t ha⁻¹ (Table 5.3). Among the evaluated models, MT-MLP achieved the highest test-set yield performance ($R^2 = 0.60$; RMSE = 3.13 t ha⁻¹), while MT-Inception and MT-TCN also demonstrated stable generalization with test R^2 values of 0.52 and 0.50, respectively. MT-ResNet achieved the strongest training performance (Train/Val $R^2 = 0.67$) but exhibited reduced generalization on the independent test dataset. Parity plots showed closer alignment with the 1:1 line and reduced scatter compared with ST yield predictions, particularly within the mid-range of observed yields (Fig. 5.4, panels a–d).

For PNN, MT produced mixed outcomes. Test-set R^2 values ranged from 0.27 to 0.64, with corresponding RMSE values between 0.27 and 0.39% (Table 5.3). The MT-TCN model achieved the highest test-set performance for N ($R^2 = 0.64$; RMSE = 0.27%), whereas MT-MLP and MT-Inception showed weaker generalization, with lower R^2 values and increased prediction error.

Relative to ST models, MT did not consistently improve PNN prediction accuracy across architectures, and in several cases resulted in greater dispersion and mild prediction bias around the 1:1 line, particularly at higher PNN concentrations (Fig. 5.4, panels e-h).

Table 5.3. Performance of multi-task (MT) deep learning models for the simultaneous prediction of potato tuber yield (t ha^{-1}) and petiole NO_3^- -N (PNN, %). Model performance is reported for the combined training/validation (Train/Val) dataset ($n = 146$) and an independent test dataset ($n = 26$) using the coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and ratio of performance to deviation (RPD).

Model	Variable	Dataset	R^2	RMSE	MAE	RPD
MT-MLP	Yield	Train/Val	0.54	3.01	2.30	1.48
		Test	0.60	3.13	2.59	1.60
	PNN	Train/Val	0.61	0.35	0.27	1.61
		Test	0.35	0.37	0.29	1.26
MT-TCN	Yield	Train/Val	0.56	2.93	2.24	1.52
		Test	0.50	3.48	2.81	1.44
	PNN	Train/Val	0.72	0.30	0.24	1.90
		Test	0.64	0.27	0.22	1.70
MT-ResNet	Yield	Train/Val	0.67	2.56	1.94	1.74
		Test	0.46	3.63	2.98	1.38
	PNN	Train/Val	0.79	0.26	0.21	2.18
		Test	0.48	0.33	0.24	1.41
MT-Inception	Yield	Train/Val	0.53	3.04	2.32	1.46
		Test	0.52	3.40	2.84	1.48
	PNN	Train/Val	0.56	0.38	0.28	1.52
		Test	0.27	0.39	0.29	1.19

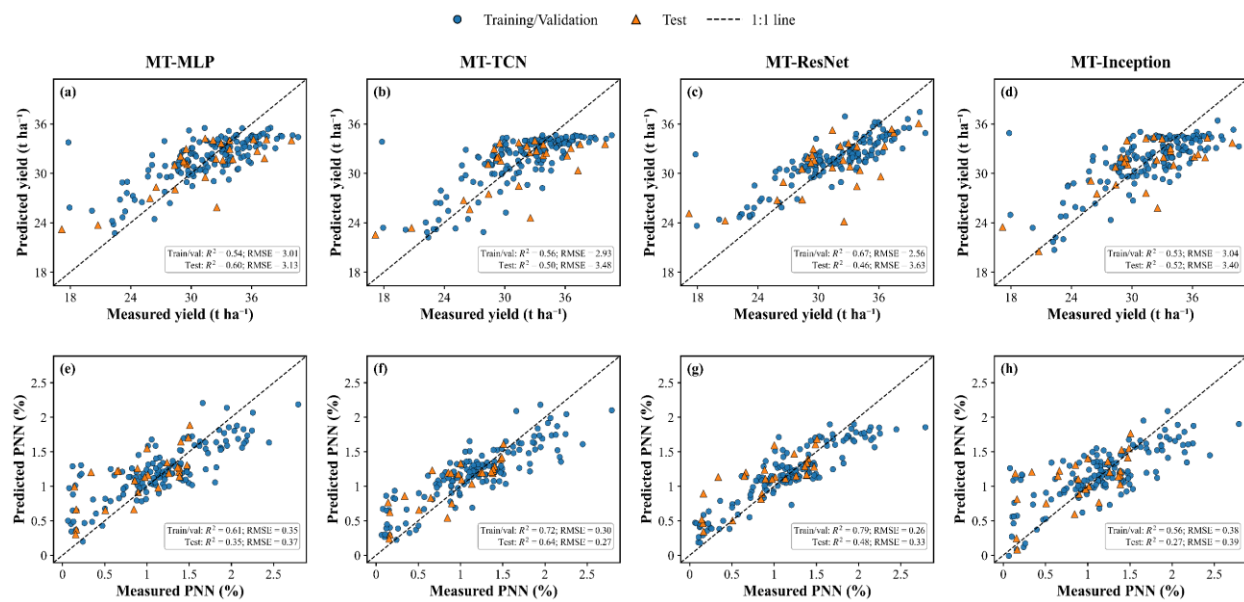


Figure 5.4. Parity plots comparing measured and predicted potato tuber yield (t ha⁻¹; a–d) and petiole NO₃⁻-N (PNN, %; e–h) obtained using multi-task (MT) deep learning models, including MT-MLP, MT-TCN, MT-ResNet, and MT-Inception. Blue circles represent training/validation samples, and orange triangles represent independent test samples. The dashed line denotes the 1:1 relationship. Model performance statistics (R² and RMSE) for the training/validation and independent test datasets are reported within each panel.

The loss-weight sensitivity analysis showed that fixed task weighting influenced the balance between yield and PNN prediction, but did not change the main interpretation of MT behaviour (Supplementary Table B1). For yield, the highest test-set performance occurred for MT-MLP at $\alpha = 0.3$ (R² = 0.63; RMSE = 2.98 t ha⁻¹), while the equal-weighted MT-MLP model showed similar performance (R² = 0.60; RMSE = 3.13 t ha⁻¹). For PNN, the strongest performance remained with MT-TCN at $\alpha = 0.5$ (R² = 0.64; RMSE = 0.27%). Increasing the yield weight to $\alpha = 0.7$ did not consistently improve yield prediction across architectures and produced variable effects on PNN performance, indicating that fixed weighting affected the balance between tasks, but the architecture- and trait-dependent behaviour observed under MT remained.

5.4.3. Residual behaviour of multi-task models

Residual diagnostics provided additional insight into the error structure and generalisation behaviour of the MT models for both response variables. For tuber yield, residuals across all MT architectures were symmetrically distributed around zero over the full range of predicted values and exhibited a relatively narrow dispersion (Fig. 5.5). No systematic bias or pronounced heteroscedastic patterns were observed, indicating that prediction errors remained largely independent of yield magnitude. The majority of residuals were confined within a limited interval, with only a small number of higher-magnitude deviations occurring at the lower and upper extremes of the yield distribution. This behaviour is consistent with the reduced RMSE values reported for MT yield prediction and suggests that joint optimisation stabilised error variance while improving predictive accuracy across yield levels.

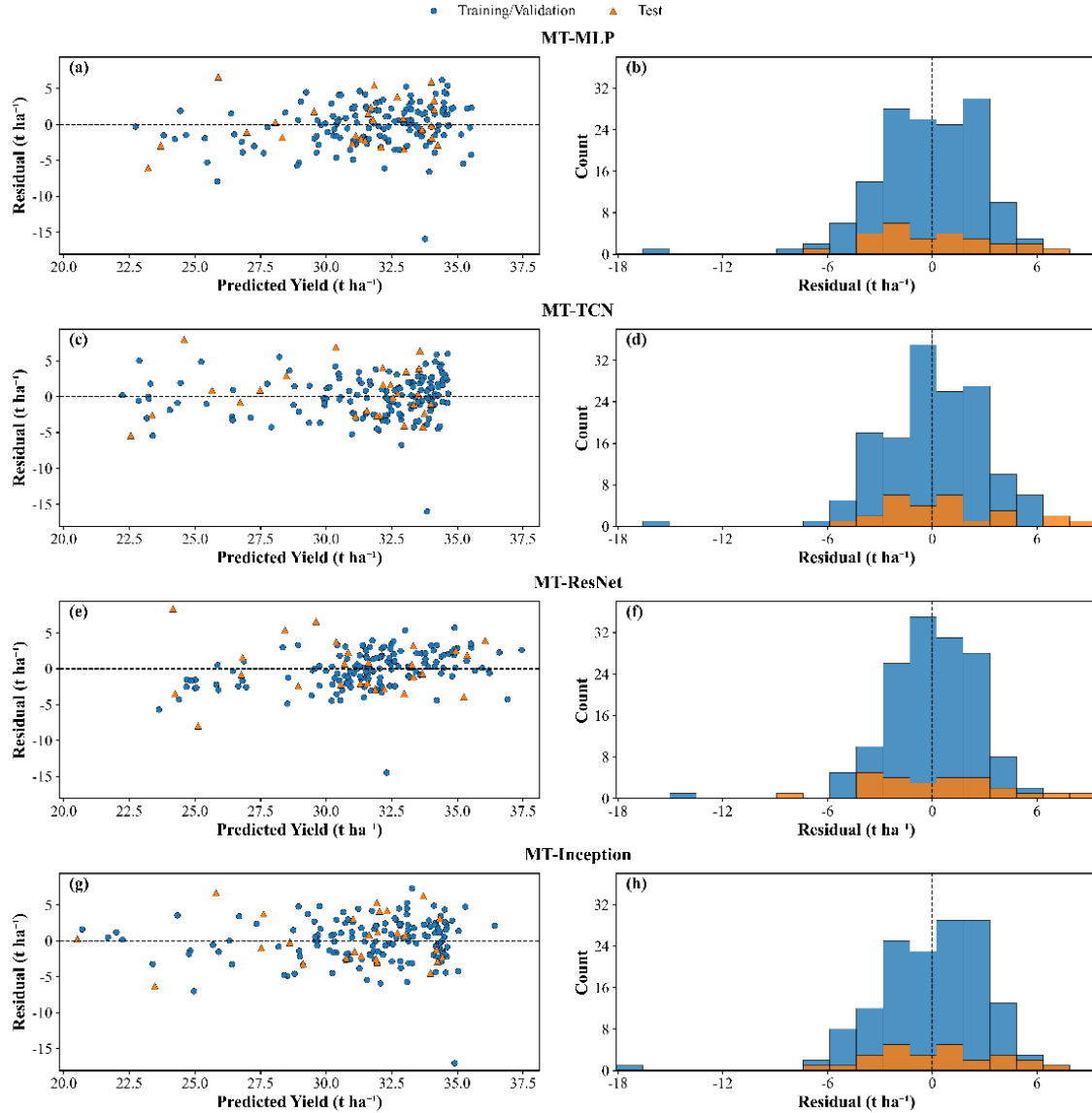


Figure 5.5. Residual plots and distributions for tuber yield predictions from multi-task (MT) deep learning models (MT-MLP, MT-TCN, MT-ResNet, and MT-Inception). Residuals are shown as a function of predicted yield (left) and as frequency distributions (right). Blue markers denote training/validation samples and orange markers denote test samples. Dashed lines indicate zero residual.

In contrast, residuals for PNN under the MT framework displayed greater dispersion and mild asymmetry relative to yield residuals, particularly at higher predicted PNN values (Fig. 5.6). Although residuals remained broadly centred around zero and did not exhibit strong heteroscedastic trends, the wider distributions indicate less constrained error behaviour for PNN

prediction within the MT framework. This pattern reflects architecture-dependent sensitivity of PNN predictions to shared feature representations and is consistent with the comparatively lower and more variable test-set performance observed for PNN across MT models.

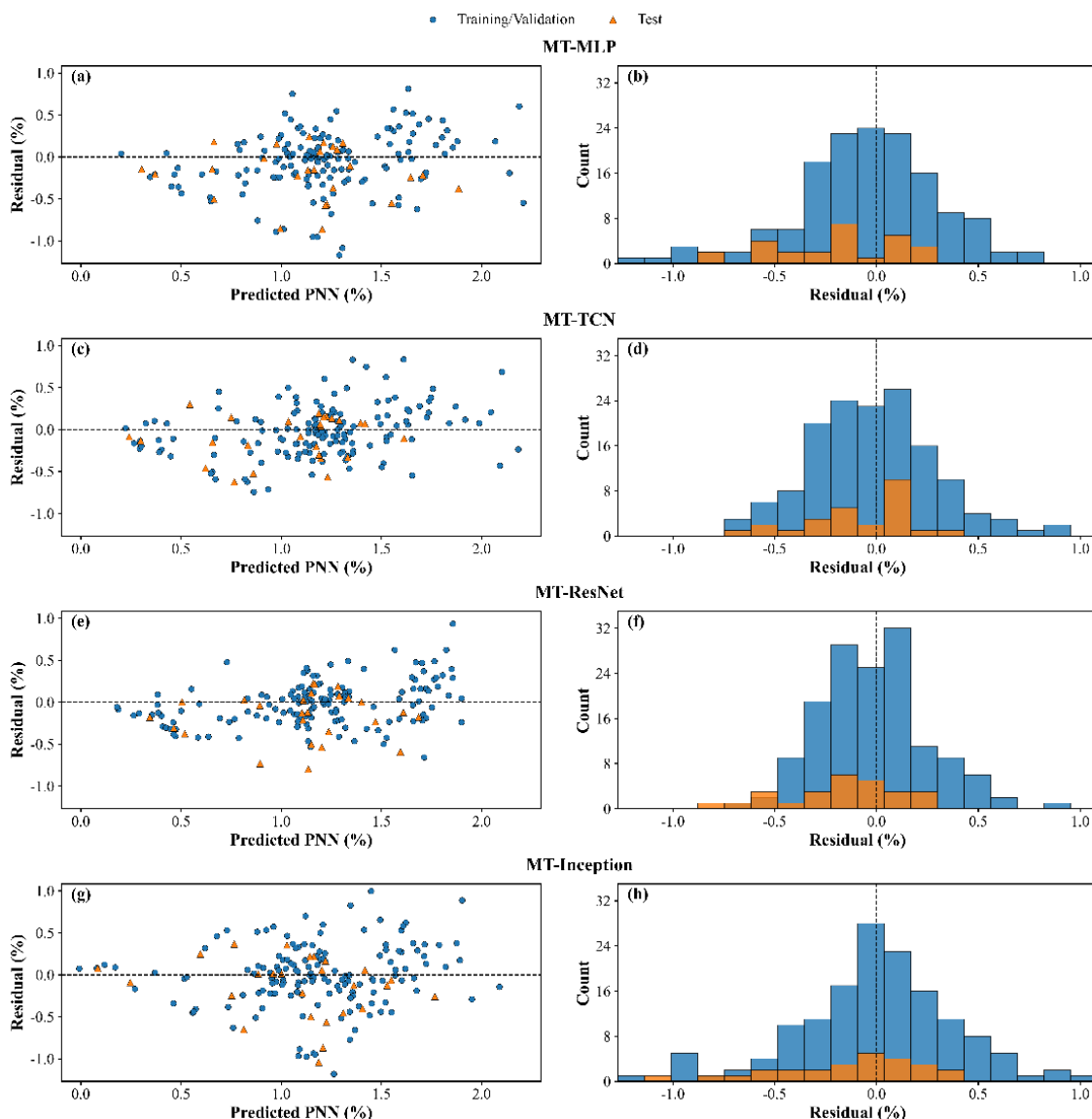


Figure 5.6. Residual plots and distributions for PNN predictions from multi-task (MT) deep learning models (MT-MLP, MT-TCN, MT-ResNet, and MT-Inception). Residuals are shown against predicted petiole NO_3^- -N (PNN) (left) and as frequency distributions (right). Blue markers represent training/validation samples and orange markers represent test samples. Dashed lines indicate zero residual.

5.4.4. Feature importance and contribution patterns

Global GradientShap analysis revealed consistent feature importance patterns across the evaluated MT architectures (Fig. 5.7). Spectral VIs exhibited the largest attribution magnitudes for both response variables, with NDVI consistently ranking as the most influential predictor for both tuber yield and PNN. Chlorophyll-sensitive indices, including Cl_green and GNDVI, also contributed strongly to model predictions, whereas LiDAR-derived canopy structural metrics showed comparatively lower but non-zero attribution values.

LiDAR-derived structural features, including upper-canopy height metrics, CV descriptors, and shape-related indices, contributed consistently across architectures for both yield and PNN prediction. Although their attribution magnitudes were smaller than those of the dominant spectral indices, the stable contributions of structural features indicate that three-dimensional canopy information provided complementary predictive information within the fused modelling framework.

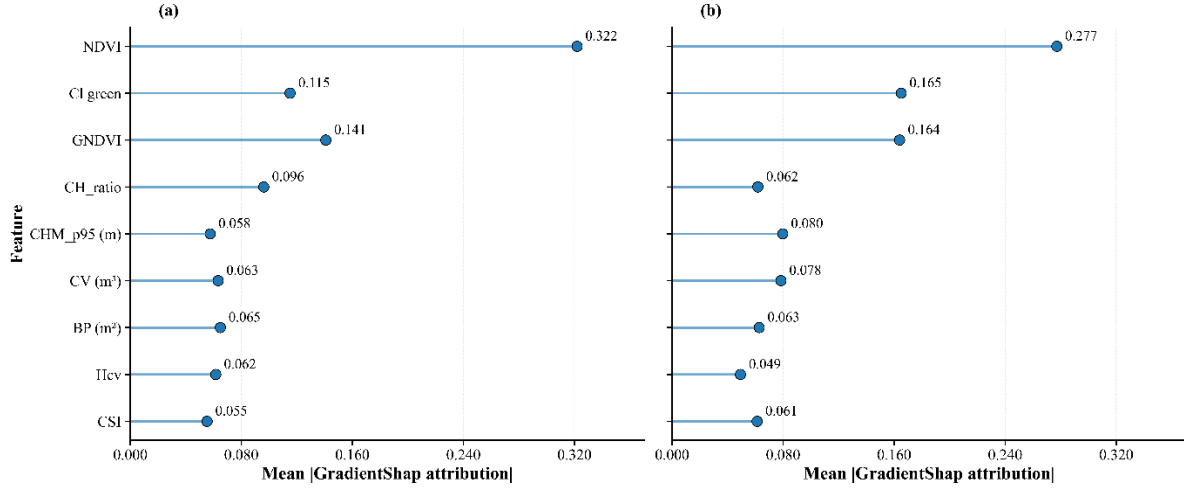


Figure 5.7. Global GradientShap feature importance for MT prediction of potato tuber yield (a) and petiole NO₃-N (PNN) (b), expressed as the mean absolute GradientShap attribution aggregated across all samples and architectures. Spectral vegetation indices and LiDAR-derived canopy structural metrics are shown in descending order of contribution magnitude.

Beeswarm GradientShap plots illustrate sample-level variability in feature effects and the directionality of each feature's contribution to model outputs (Fig. 5.8 for yield; Fig. 5.9 for PNN). For the dominant spectral indices, higher standardized values of NDVI and GNDVI more frequently aligned with positive attributions, indicating that greener canopies tended to increase predicted yield and PNN relative to the baseline, whereas lower index values were more often associated with negative attributions. In contrast, LiDAR-derived structural metrics exhibited broader and more symmetric attribution distributions around zero, with both positive and negative contributions observed across samples, reflecting context-dependent feature effects within the shared model representation.

Attribution patterns also differed between the two outputs. Relative to PNN, yield predictions showed a wider spread and more frequent non-zero contributions from structural and volumetric descriptors, whereas PNN attributions were more strongly concentrated within a smaller subset of spectral predictors. These patterns suggest partial feature sharing between tasks alongside output-

specific emphasis within the shared representation, consistent with the contrasting responses of yield and PNN observed under multi-task optimisation.

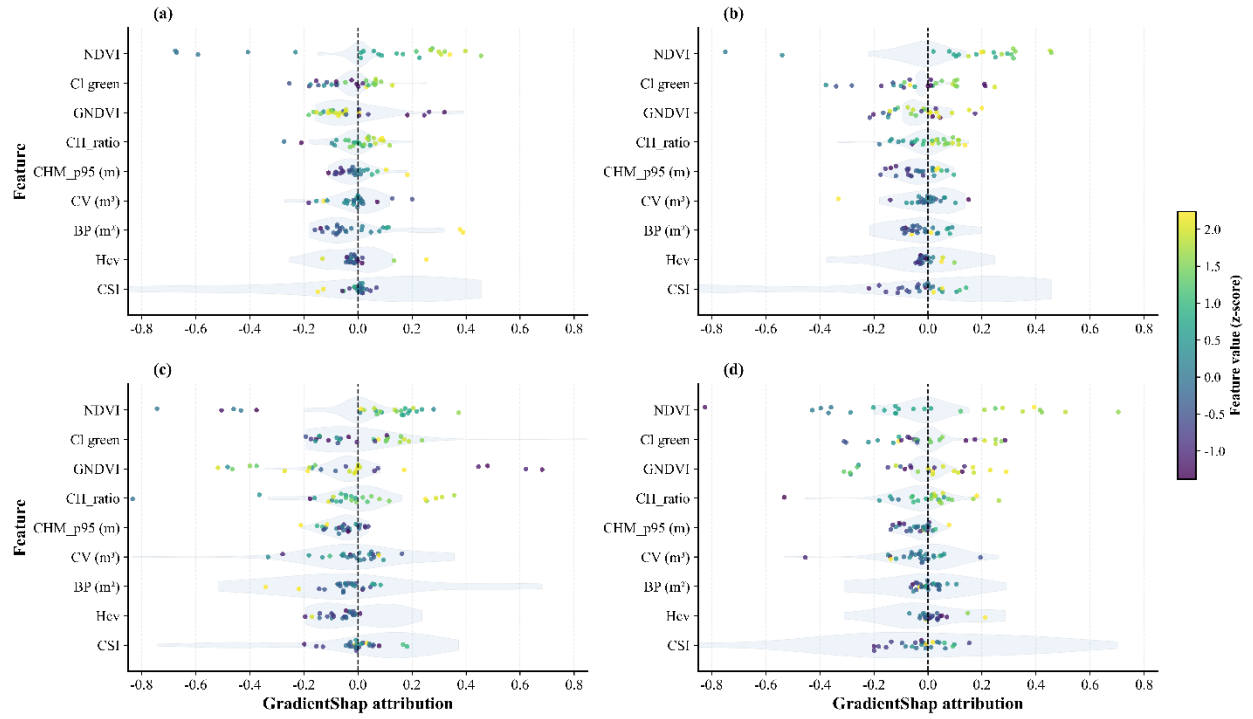


Figure 5.8. Beeswarm GradientShap attributions for multi-task (MT) prediction of potato tuber yield (t ha⁻¹) across four architectures: MT-MLP (a), MT-TCN (b), MT-ResNet (c), and MT-Inception (d). Each point represents a plot-level observation from the independent test dataset, coloured by standardized feature value (z-score). The horizontal axis indicates attribution magnitude and direction, with the dashed vertical line denoting zero contribution.

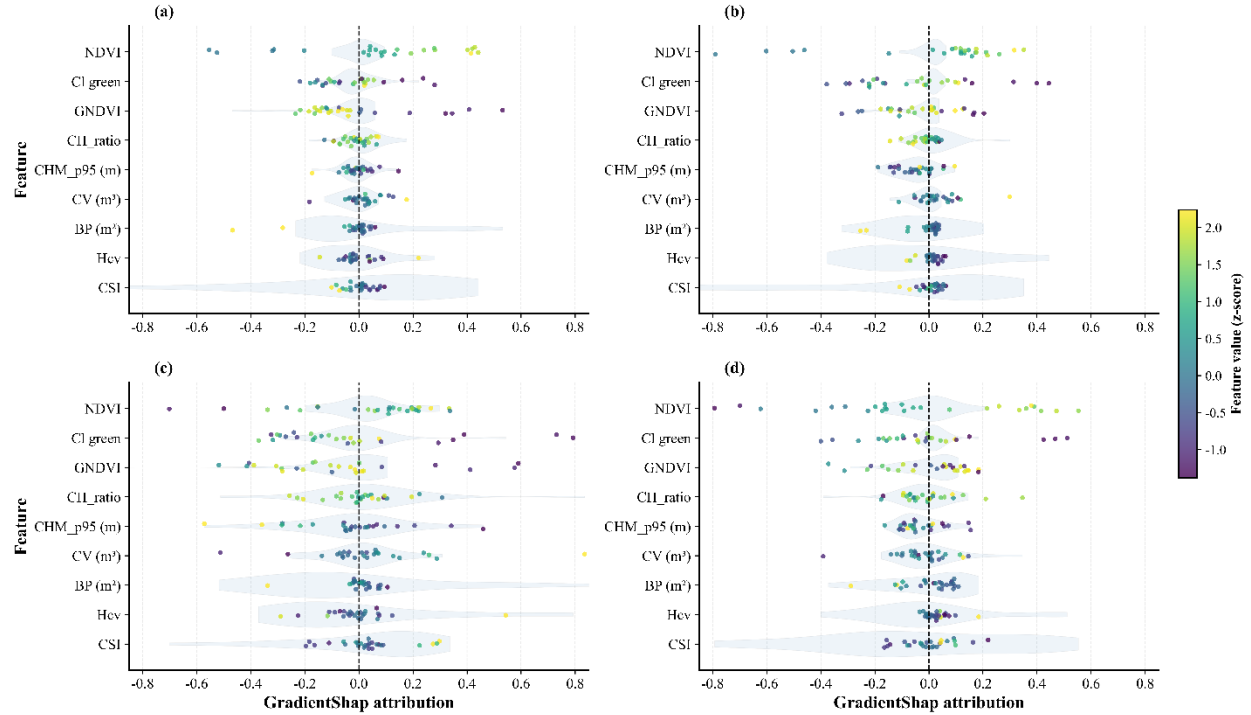


Figure 5.9. Beeswarm GradientShap attributions for multi-task (MT) prediction of petiole NO_3^- -N (PNN, %) across the same four architectures shown in Fig. 5.8. Plot-level observations from the independent test dataset are coloured by standardized feature value (z-score). The horizontal axis represents attribution magnitude and direction, with zero contribution indicated by the dashed vertical line.

5.5. Discussion

5.5.1. Prediction of yield and nitrogen from fused UAV observations

The contrasting predictive performance observed for tuber yield and PNN reflects fundamental differences in how these variables are expressed at the canopy level and how effectively they can be inferred from RS observations. Under the ST framework, PNN was predicted with relatively high accuracy and stability across architectures, with test-set R^2 reaching up to 0.71. This performance indicates that crop N status at row closure was strongly encoded in canopy spectral properties captured by UAV-based MS observations. PNN is closely linked to leaf chlorophyll concentration and photosynthetic activity, which directly influence canopy reflectance in the

visible and near-infrared spectral regions, making N status a physiologically proximal variable that is readily observable through MS data at this stage of development.

In contrast, ST prediction of tuber yield remained consistently limited, with test-set R^2 values below 0.26 across all evaluated architectures. Unlike PNN, yield represents an integrative outcome of cumulative growth processes, including canopy expansion, radiation interception, biomass accumulation, and assimilate partitioning over the growing season. While spectral and structural features derived at row closure capture important aspects of canopy status, these observations provide only a partial representation of the processes governing final yield, constraining the extent to which yield variability can be inferred from a single phenological snapshot. Similar behaviour has been reported in studies examining joint prediction of yield and physiological traits, where integrative variables such as yield exhibit stronger dependence on cumulative or temporally resolved RS information, whereas physiologically proximal traits show more direct associations with canopy biochemical signals (Z. Sun et al., 2022).

The limited performance of yield-only ST models in the present study therefore reflects the integrative nature of yield formation and its weaker physiological proximity to instantaneous canopy measurements, rather than deficiencies in sensor resolution or modelling capacity. This distinction highlights the importance of jointly considering trait physiology and the temporal representativeness of RS inputs when evaluating the predictive potential of UAV-based data for agronomic applications.

5.5.2. Effects of MT on joint prediction performance

Joint optimisation of yield and PNN resulted in a clear divergence in learning behaviour between the two response variables. Across all architectures, MT substantially improved tuber yield prediction relative to ST baselines. Test-set yield R^2 values increased from a maximum of 0.26

under ST to values between 0.46 and 0.60 under MT, accompanied by consistent reductions in RMSE. Parity plots further demonstrated reduced scatter and improved alignment with the 1:1 line compared with ST yield predictions. These improvements indicate that shared learning enabled the models to exploit complementary spectral and structural information, yielding latent canopy representations that were more informative for cumulative yield formation than those learned under yield-only optimisation. Similar stabilising effects of MT on yield prediction have been reported in UAV-based DL studies, where shared representations enhanced generalisation for integrative agronomic traits (Chang et al., 2024).

In contrast, PNN prediction did not consistently benefit from joint learning. While the MT-TCN architecture retained relatively strong PNN prediction performance (test $R^2 = 0.64$), other MT models exhibited reduced accuracy relative to their ST counterparts. Parity plots and residual diagnostics revealed increased dispersion of PNN prediction errors across MT architectures, particularly at higher N concentrations. This behaviour is consistent with partial task interference, whereby shared feature representations optimised to support yield prediction may reduce the model's capacity to preserve fine-scale spectral information critical for accurate PNN estimation. Because N concentration is governed primarily by biochemical properties of foliage, its prediction depends on retaining sensitivity to subtle spectral variations, which may be attenuated when joint optimisation prioritises structural gradients associated with yield. This pattern is compatible with task interference in MT settings, where a shared representation that is beneficial for one target can be sub-optimal for another, producing task-dependent gains and even negative transfer (Fathi et al., 2025). The contrasting PNN response can also be interpreted through how the two prediction heads used the shared latent space. Recent work has shown that MT behaviour can depend not only on broad task relatedness, but also on how task-specific heads draw information from this

shared space (D. Mao et al., 2024). In this study, yield benefited from a broader MS–LiDAR representation that combined spectral vigour with canopy structure, whereas PNN depended more narrowly on chlorophyll-sensitive spectral variation. The inconsistent PNN response under MT therefore points to representational competition, rather than a lack of agronomic connection between yield and PNN.

5.5.3. Contribution of canopy structural information to yield prediction

LiDAR-derived canopy structural metrics contributed consistently to tuber yield prediction, particularly within the MT framework; however, their lower GradientShap magnitudes relative to spectral indices indicate that their role was complementary rather than primary. This distinction is important for interpreting sensor fusion in this study. Spectral indices captured the dominant row-closure signal associated with canopy vigour and chlorophyll-related status, whereas LiDAR metrics represented a different measurement domain: three-dimensional canopy architecture, including upper-canopy height, canopy volume, and canopy heterogeneity. The added value of LiDAR therefore lies in describing structural variation that is only indirectly represented in multispectral reflectance, not in replacing spectral predictors as the main source of model signal.

This interpretation is consistent with multi-sensor crop-yield studies showing that different RS data streams can contain both shared and unique information, and that fusion benefits often arise from the non-redundant component contributed by each sensor rather than from equal feature importance across modalities (Guan et al., 2017). In the present study, LiDAR-derived height and volumetric metrics provided architectural context for yield prediction by encoding vertical structure and within-plot heterogeneity associated with biomass accumulation and resource capture. Similar contributions of LiDAR-based structural metrics to yield prediction have been reported in multi-sensor UAV studies, where canopy height and volumetric descriptors improved

representation of crop development beyond spectral indices alone (Maimaitijiang et al., 2020; F. Zhang, Hassanzadeh, et al., 2025). Under MT learning, this structural contribution was more relevant to yield than to PNN, confirming that LiDAR mainly supported the cumulative growth component of the shared model rather than the physiologically proximal N response.

The LiDAR attribution pattern under MT yield prediction is best interpreted as conditional feature use within the fused model, not as evidence that structural metrics independently drove yield differences. GradientShap is conceptually aligned with additive attribution approaches such as SHAP, which assigns feature-level contributions to model predictions (Lundberg & Lee, 2017). This distinction is important because spectral indices and LiDAR metrics were derived from the same row-closure canopy and were therefore not independent inputs; when predictors are dependent, Shapley-based explanations can distribute importance across correlated variables in ways that reflect the model's learned feature use rather than separable agronomic effects (Aas et al., 2021). In the MT framework, the PNN task likely anchored much of the chlorophyll-sensitive spectral signal, allowing the yield head to draw more visibly on LiDAR-derived height, volume, and heterogeneity as structural proxies for residual yield-related variation. The resulting attributions should therefore be viewed as biologically interpretable predictive associations within the experimental N-treatment gradient, not as direct causal effects.

5.5.4. Task-specific feature reliance from attribution analysis

GradientShap attribution analysis revealed clear task-dependent differences in how input features were utilised for yield and PNN prediction. While spectral VIs contributed strongly to both outputs, the structure of feature reliance differed markedly between tasks. NDVI, along with chlorophyll-sensitive indices such as *Cl_green* and *GNDVI*, exhibited consistently directional attributions for PNN, indicating concentrated dependence on a limited set of spectral predictors.

In contrast, yield prediction relied on a broader and more heterogeneous combination of spectral and structural features. LiDAR-derived structural metrics exhibited distributed attribution patterns with both positive and negative contributions across samples, reflecting non-linear and context-dependent effects associated with spatial canopy organisation. These patterns suggest that yield prediction under both ST and MT frameworks draws on interactions between canopy spectral status and three-dimensional structure, rather than on a small subset of dominant predictors alone. Comparable distinctions between structural and spectral drivers have been reported in interpretable UAV-based yield modelling studies, where LiDAR-derived canopy height and volumetric metrics contributed to yield through non-linear and stage-dependent pathways that were distinct from chlorophyll-sensitive spectral indices (F. Zhang, et al., 2025).

5.5.5. Architecture-dependent learning behaviour

Model architecture exerted a clear influence on predictive stability and generalisation under both ST and MT learning. Under MT optimisation, architectures with more constrained parameterisation and controlled feature interactions, such as the MLP and TCN, exhibited more consistent generalisation for yield prediction. In contrast, more expressive architectures achieved stronger training performance but showed larger performance degradation on the independent test dataset. This pattern was most pronounced for the MT-ResNet model, which attained the highest training R^2 for yield but exhibited reduced test-set performance, indicating increased sensitivity to overfitting under shared optimisation.

Architecture-dependent effects were most clearly expressed for yield prediction, whereas PNN performance showed less systematic variation across architectures, reflecting its stronger dependence on spectrally driven features rather than model capacity. These observations are consistent with architecture-dependent trade-offs reported in MT-DL settings, where model

generalisation is sensitive to both task relatedness and the design of shared representations (Keceli et al., 2022). In the present study, architectures emphasising constrained interactions and implicit regularisation were better suited to joint learning, whereas highly expressive networks appeared more sensitive to the balance between shared and task-specific representations.

5.5.6. Implications for precision nitrogen management

The joint estimation of tuber yield and PNN from a single UAV sensing campaign provides complementary information on crop productivity and nutritional status at row closure. Although PNN prediction did not consistently improve under MT learning, the observed improvement in yield prediction under joint optimisation indicates that yield variability at this stage is more strongly associated with integrated canopy development than with N status alone. Spatial patterns characterised by adequate PNN but limited structural development may therefore reflect zones where yield is constrained by factors other than N availability, highlighting situations in which canopy structure provides additional context beyond nutrient indicators.

This integrated perspective is consistent with the objectives of precision nutrient management, which emphasise accounting for spatial variability in crop response and management requirements through multi-dimensional information rather than reliance on single nutrient indicators in isolation (Y. Zhang et al., 2023). The combined use of MS and LiDAR observations offers a framework for interpreting spatial differences in crop status by jointly considering canopy biochemical and structural attributes, thereby supporting more informed assessment of within-field variability at key phenological stages.

5.5.7. Practical considerations and limitations

The analysis was conducted at the plot scale and focused on a single phenological stage, which constrains inference to spatial variability expressed at row closure rather than to the full temporal trajectory of yield formation. This design was intentional, as row closure is a practical decision point for assessing canopy development and in-season N status; however, final tuber yield is influenced by canopy development, growth stage, and environmental conditions across the season (Y. Fan, Liu, et al., 2024). Canopy spectral and structural responses later in the growing season may therefore introduce additional controls on yield formation that are not represented within the present framework. In addition, reliance on plot-level aggregation of spectral and structural features may obscure within-plot heterogeneity and fine-scale canopy variation that could influence yield and N responses under more heterogeneous field conditions.

Although the dataset was modest for DL, it was based on two growing seasons, a structured N treatment gradient, and plot-level reference measurements for both tuber yield and PNN. The independent test set was also limited in size; therefore, the results should be interpreted as a controlled comparison of MT and ST learning strategies within the sampled fields, cultivar, seasons, and management conditions, rather than as a fully transferable operational model. The study was also limited to Russet Burbank under irrigated production conditions. Cultivar growth habit and water status may alter the canopy signals used by the model, including greenness, temperature-related stress expression, canopy development, and yield response. Potato studies under water-restricted conditions have shown that canopy temperature and leaf greenness responses can vary by cultivar and growing environment (Hill et al., 2024), while simulation studies of water-limited potato yield indicate that cultivar- and context-specific responses can affect model transfer across locations, soils, and water-availability conditions (ten Den et al.,

2024). Model transfer to other cultivars or water-stress conditions should therefore be evaluated through external validation rather than assumed from the present irrigated Russet Burbank dataset. Given that DL performance in agricultural tabular datasets is sensitive to architecture choice, preprocessing, and validation design (Richetti et al., 2023), broader evaluation across multi-site and multi-cultivar datasets is needed to assess model robustness. Such work should also examine temporal transferability across multiple growth stages, reduced or alternative sensing configurations, and scalability under commercial field conditions. Recent reviews of LiDAR applications in precision agriculture have emphasised both the value of three-dimensional structural information for crop assessment and the need for more efficient acquisition and processing workflows to support operational deployment (Rivera et al., 2023). Extending the present framework along these dimensions would help clarify its robustness and operational relevance across a wider range of production systems.

5.6. Conclusion

This study examined the application of MT-DL to the joint prediction of potato tuber yield and PNN using fused UAV-derived MS and LiDAR data acquired at a consistent phenological stage across two growing seasons. By analysing yield and PNN within a shared modelling framework, the work highlights how traits governed by different physiological timescales are differentially encoded when spectral and three-dimensional structural information are learned jointly. The findings indicate that yield prediction benefits from representations that integrate canopy spectral responses with structural descriptors capturing cumulative growth and spatial organisation, whereas N prediction remains more strongly associated with spectrally derived indicators of foliar biochemical status. This divergence reflects differences in how yield and N status respond to

canopy architecture, with cumulative traits drawing greater benefit from structural context than physiologically proximal indicators. The results further indicate that model architecture influences the balance between representational flexibility and generalisation under joint optimisation, particularly when task relationships are only partially aligned. Overall, the results indicate that performance gains from multi-task learning in precision agriculture are conditional, depending on alignment between sensing modality, model capacity, and the physiological controls governing each target trait, rather than on joint optimisation alone.

5.7. References

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Chapter 6

General Discussion and Conclusions

6.1. Overall synthesis of findings

Potato nitrogen (N) assessment and yield prediction were evaluated through a progression from evidence synthesis to field-based analysis of sensing approaches with increasing spectral and structural complexity. Predictive performance was shaped less by sensing complexity alone than by how closely the sensed information matched the biological and observational character of the target trait. The central distinction was therefore not between simpler and more advanced platforms, but between sensing configurations that were physiologically well matched to the response variable and those that were not. In that sense, the dissertation does not support a single-sensor view of potato monitoring. Rather, it supports a trait-specific interpretation in which multispectral, hyperspectral, and fused spectral-structural approaches each occupy distinct but complementary roles within a broader precision agriculture framework.

The review chapter established the broader context for this interpretation by showing that, despite the agronomic and economic importance of potato in Canada, research integrating remote sensing (RS), proximal sensing, and predictive modelling for potato N and yield management remains comparatively limited and unevenly distributed. That chapter did more than summarize previous work. It identified a clear gap in the Canadian evidence base and provided the conceptual basis for the empirical chapters that followed. The dissertation responded to that gap by moving beyond general discussion of technological potential and toward direct evaluation of how different sensing modalities behave when applied to specific potato traits under Manitoba conditions. In doing so, it shifted the focus from whether sensing-based approaches are promising to the more important question of how, and under what conditions, they become informative for potato monitoring.

The multispectral chapter showed that unmanned aerial vehicle (UAV)-based multispectral imagery can provide useful in-season information for potato N assessment when feature selection is treated as part of the modelling problem rather than as a preliminary technical exercise. Chlorophyll-sensitive and red-edge-related vegetation indices (VIs) carried meaningful information on petiole NO_3^- -N status, with CI green emerging as a particularly informative predictor, but model performance depended not only on algorithm choice, but also on how the predictor space was filtered before calibration. The significance of that result lies in what it implies about limited-band sensing more generally. The value of multispectral imagery resided less in raw band availability than in the disciplined extraction of the spectral information most closely linked to foliar biochemical condition. Under those conditions, UAV-based multispectral sensing proved capable of supporting in-season discrimination of variation in potato N status, while also showing that analytical discipline remained central to extracting useful signal from a constrained spectral domain. Quantitatively, however, that usefulness remained moderate rather than exhaustive. The best multispectral configuration in this dissertation, obtained with Random Forest (RF) after Recursive Feature Elimination (RFE)-based variable selection, reached an R^2 of 0.571 with an MAE of 0.365%, while the strongest individual VI relationships with petiole NO_3^- -N peaked at $r = 0.75$ for CI green and $r = 0.73$ for GNDVI. This is important because it shows that the practical value of multispectral sensing lay not in fully resolving crop N status, but in extracting a disciplined and agronomically responsive signal from a limited spectral space.

The hyperspectral chapter extended this line of inquiry by showing that visible and near-infrared to shortwave infrared (VNIR-SWIR) hyperspectral spectroscopy provided a richer representation of N-related spectral behaviour than multispectral imagery, particularly when measurements were acquired under controlled conditions. Spectral information in the visible and shortwave infrared

regions was especially relevant to N prediction, and the one-dimensional convolutional neural network (1D-CNN) was effective in learning these relationships across measurement datasets. At the same time, the chapter made clear that greater spectral richness does not remove the importance of acquisition context. Prediction was strongest for laboratory fresh-leaf spectra and less stable for field canopy measurements, where illumination effects, viewing geometry, and canopy-level interference introduced additional variability. The improvement obtained through calibration transfer was therefore especially important, because it showed that part of the gap between controlled and field measurements can be reduced through appropriate spectral alignment. The broader implication is that hyperspectral sensing offers greater biochemical specificity than multispectral sensing, but that advantage is realized most effectively when the measurement environment is controlled or when the analytical workflow explicitly compensates for field-induced distortion. That distinction was also visible numerically. The best field hyperspectral model in Chapter 4, a 1D-CNN, achieved $R^2 = 0.77$ with $RMSE = 0.27\%$, whereas the best laboratory fresh-leaf configuration reached $R^2 = 0.90$ with $RMSE = 0.22\%$. After calibration transfer, field-based 1D-CNN performance improved further to $R^2 = 0.82$ with $RPD = 2.35$. Although these values were obtained under a different measurement design than the UAV multispectral analysis and should therefore not be treated as a strict head-to-head comparison, they still indicate that broader spectral sampling materially strengthened N estimation when measurement conditions and calibration were properly managed.

The fused light detection and ranging (LiDAR)–multispectral chapter extended the dissertation from N assessment alone to the joint prediction of N and tuber yield within single-task and multi-task deep learning frameworks. The results indicated that yield and petiole NO_3^- -N were not represented in the canopy in the same way and did not benefit equally from shared modelling. The

clearest advantage of the fused LiDAR–multispectral framework was observed for tuber yield, where multi-task learning achieved a test-set R^2 of 0.60. By comparison, the best multi-task prediction for petiole NO_3^- -N reached $R^2 = 0.64$, but this advantage was less consistent across architectures. This contrast suggests that shared learning contributed more to yield prediction than to N estimation. Yield prediction improved more clearly when spectral information was complemented by structural descriptors, consistent with yield being a cumulative end-of-season outcome shaped by canopy development and integrated crop growth over time. In contrast, petiole NO_3^- -N remained more closely associated with spectrally derived indicators of foliar condition. Attribution analyses reinforced this distinction by showing broader structural and volumetric dependence for yield, but narrower spectral dependence for N. This chapter therefore indicates that sensor fusion and multi-task learning are not inherently advantageous; their value depends on whether the shared representation corresponds meaningfully to the biological relationship between the prediction targets. More broadly, the findings suggest that increasing model complexity is justified only when it is accompanied by a genuine increase in biologically relevant information.

The central synthesis is not that more complex sensors or models are always better, but that prediction quality depends on alignment among trait physiology, sensing modality, acquisition context, and modelling design. Under the Manitoba conditions examined here, that alignment became clearer as the analysis progressed from narrow-band canopy proxies to chemically richer spectral measurements and then to integrated spectral-structural representations. Together, these results clarify how sensing-based approaches can contribute to potato N assessment and yield prediction and show that stronger progress comes from matching the form of sensed information to the biological character of the prediction target. In that sense, the dissertation contributes not only empirical findings, but also a clearer interpretive basis for how sensing systems should be

evaluated in potato research. That synthesis establishes the foundation for the methodological, practical, and forward-looking discussion that follows.

6.2. Methodological implications

Model performance was strongly conditioned by study design, measurement domain, and evaluation strategy. Across the empirical chapters, the main methodological issues were feature redundancy in multispectral modelling, domain instability between field and laboratory hyperspectral measurements, and the challenge of evaluating fused spectral-structural models under restricted temporal sampling. This matters because recent work on in-season yield prediction and model transferability shows that predictive performance is often governed by factors beyond the technical strength of the modelling framework itself. These include prediction lead time, phenological alignment, regional transfer, and the spatial context within which model relationships are developed and evaluated (Franch et al., 2026; Z. Liu et al., 2026).

The multispectral analysis (Chapter 3) sharpened this point by showing that, in limited-band systems, feature construction belongs to the inferential core of the study rather than to its technical margins. Once VIs are accumulated too freely, the analytical task can shift from isolating biologically meaningful signal to managing redundancy, so that apparent gains in performance begin to reflect repeated encoding of closely related spectral behaviour rather than genuinely new information. In that respect, the results argue for a stricter understanding of parsimony in multispectral sensing. What matters is not the sheer number of indices available, but whether the retained variables preserve physiological specificity and avoid collapsing the predictor space into multiple versions of the same canopy response. That caution is consistent with research showing that N retrieval from reflectance remains constrained by the difficulty of separating the target

signal from correlated variation in pigments, water status, and structural properties, while no single standard spectral index has achieved robust generality across datasets (Wan et al., 2022).

The hyperspectral chapter brought a different methodological issue into view. There, the problem was not shortage of predictor information, but instability introduced by the measurement domain itself. Field canopy spectra, laboratory fresh-leaf spectra, and laboratory dried-leaf spectra cannot be assumed to occupy the same inferential space, even when they are used to estimate the same underlying trait. That point has important consequences for study design. Robustness across domains cannot be treated as a secondary refinement added after calibration; it has to be built into the sensing framework from the outset. Recent studies support this interpretation from different directions: physically informed hyperspectral modelling has been shown to generalize more robustly to unseen data than purely empirical calibration alone, while transferability has also improved when spectral information is integrated with auxiliary environmental covariates, such as temperature, precipitation, and soil moisture, rather than used in isolation (Chakraborty et al., 2025; Cui et al., 2026). In methodological terms, this means that spectral richness by itself is not enough. The conditions under which spectra are acquired remain central to whether predictive strength can be carried across domains.

A further implication concerns evaluation. This dissertation suggests that assessment procedures in agricultural RS too often reward apparent fit more readily than predictive stability. This becomes especially problematic when predictor space is compressed, temporally incomplete, or transferred beyond the domain in which it was learned. As the Chapter 5 results indicated, strong average fit can coexist with weakening agronomic discrimination at the edges of the response range. Recent studies suggest that this issue is not isolated. In dense vegetation, part of the apparent saturation problem can arise from the mathematical form of NDVI itself (Z. Tian et al., 2025), while

phenology-aware and structurally enriched yield pipelines have outperformed purely spectral approaches by representing crop development more explicitly over time (Athar et al., 2026). Under data-limited conditions, transfer learning has also reduced performance losses in cross-scale yield prediction (J. Zhang et al., 2025). The methodological question, therefore, is no longer only whether a model achieves a strong overall score, but whether it retains discrimination when the observational problem becomes biologically and statistically difficult.

Interpretability should be understood in the same way. Once sensing workflows become more complex, explanation cannot remain a decorative appendix to prediction. It has to function as a validity check on whether the model is relying on defensible crop information, whether feature importance is stable enough to be trusted, and whether the fitted relationships remain agronomically interpretable. The attribution analyses in this dissertation brought that issue into focus by showing that structural and spectral variables did not contribute equally across prediction targets, and that this asymmetry was biologically meaningful rather than incidental. Recent review work has made a similar point, emphasizing that explainable artificial intelligence becomes methodologically valuable in agricultural spectroscopy not when it merely visualizes model behaviour, but when it improves confidence in how spectral information is being used and interpreted (Ahmed et al., 2025). Under that view, interpretability is not an optional add-on. It becomes part of the methodological test of whether a predictive model is agronomically credible.

These points suggest that methodological progress in potato sensing research will depend less on choosing increasingly sophisticated algorithms in isolation and more on building coherent sensing frameworks in which trait physiology, sensing modality, measurement domain, model structure, evaluation strategy, and interpretability are aligned from the start. The dissertation therefore points

toward a more integrated basis for judging when a sensing approach is methodologically appropriate for a particular agronomic target under field conditions.

6.3. Practical implications for potato N assessment and yield prediction

The practical significance of this dissertation lies not in replacing agronomic diagnosis, but in using spatial crop information to identify where additional sampling or scouting is needed while there is still time to act. In that respect, the main value of sensing is not simply that it produces additional information, but that it changes how crop variability can be recognized within the field and how diagnostic effort can be directed in response. For potato N assessment, this matters because conventional tissue-based methods remain agronomically credible, yet their point-based nature limits their ability to represent the full spatial pattern of crop condition. The findings therefore support the use of sensing as a way to improve where attention is directed, where sampling is intensified, and where interpretation should be more cautious.

One practical consequence is that potato N assessment is better approached as a problem of within-field prioritization than as an exercise in uniform field characterization. Under commercial conditions, the agronomic difficulty is often not the absence of information, but uncertainty about where the most consequential variation lies and whether it is large enough to justify further inspection or intervention. Because critical PNN concentrations decline with crop development, the threshold is stage-specific; at approximately 60 days after planting, concentrations below 1.11% on a dry-weight basis represent a high probability of N deficiency and warrant the greatest attention, while concentrations between 1.11 and 1.80% indicate a moderate probability (Giletto et al., 2026). For application in Manitoba, this decision range should be locally calibrated for

Russet Burbank against crop response before being used to guide targeted sampling or in-season N management.

The present work shows that UAV multispectral sensing is most useful in this setting when it identifies spatial differences in crop condition while the crop is still within a responsive stage. Its practical role is therefore strongest when used to guide tissue sampling, scouting, and zone-based interpretation rather than when used as a direct stand-alone substitute for established measurements. Used in that way, sensing does not displace field knowledge; it extends it across space.

The dissertation also indicates that management purpose should determine sensing depth. Multispectral sensing is the more realistic field-level option for routine in-season surveillance because it provides useful sensitivity to crop condition in a form that is operationally accessible. Hyperspectral sensing belongs in a different practical category. Its greatest value lies in situations where stronger biochemical discrimination is needed, where the interpretation of canopy response is uncertain, or where broader sensing requires a higher-confidence diagnostic layer. In that sense, hyperspectral measurement is better positioned as a selective diagnostic and calibration tool than as the default platform for every field and every management question. That distinction is practically important because it places each sensing approach where its operational value is most credible rather than assuming that richer data are automatically more useful.

A further practical issue concerns how sensing products should be read once the crop reaches vigorous canopy development. At that stage, the optical response of the canopy becomes less reliable as a precise linear surrogate across the full biological range and more useful as an indicator of relative field condition. This changes the way sensing outputs should be interpreted. Their strongest practical value is no longer in assigning a stable physiological estimate to every location,

but in identifying comparative patterns, response zones, and anomalous areas that justify closer agronomic attention. That distinction matters because many management decisions in potato production depend less on recovering an exact value at every point than on separating normal from atypical crop behaviour and directing effort toward the parts of the field most likely to influence outcome.

The same logic applies to yield, but in a different way. The dissertation shows that end-of-season productivity cannot be interpreted from N-sensitive spectral response alone. Structural information becomes practically relevant because it broadens the representation of crop performance beyond foliar condition and places yield variability within a wider developmental context. This does not mean that every additional sensing layer will produce a major gain in operational value. It means that yield interpretation becomes more credible when crop condition is read through both spectral and structural evidence rather than through N-sensitive indicators alone. Practically, that supports a more restrained interpretation of within-field yield variability and reduces the risk of attributing productivity differences too narrowly to nutrition when broader canopy-development processes may be involved.

Timing is equally important. The usefulness of sensing depends not only on predictive strength, but on whether the information is acquired at a stage when it can still influence management. For potato N assessment, its value is greatest when it supports interpretation while the crop retains meaningful capacity to respond. For yield, the same sensing window serves a different purpose. It becomes less intervention-oriented and more interpretive, helping reveal how productivity variability is organising across the field and how that variability relates to canopy expression. The practical lesson is that sensing campaigns should be designed around response opportunity rather

than around data collection alone. Information acquired outside the window of action may still be analytically informative, but it is less valuable agronomically.

At farm scale, these findings support a layered operational strategy rather than a single-platform solution. A practical workflow begins with broad field surveillance to detect spatial variability and then proceeds to more targeted diagnostic escalation where uncertainty remains high. When the management question extends beyond nutrient condition to productivity pattern, the workflow can then shift toward structurally informed interpretation. The strength of this logic is that it aligns sensing intensity with management need. It does not ask one tool to answer every agronomic question. Instead, it assigns each sensing approach a role that reflects its most defensible practical advantage: broad spatial screening from multispectral imagery, more selective diagnostic refinement from hyperspectral measurement, and added developmental context from LiDAR where productivity interpretation requires it.

The practical direction emerging from this dissertation is therefore one of selective integration rather than technological substitution. For potato N assessment, the most immediate gain is better targeting of within-field diagnosis. For yield prediction, the main gain is a more credible interpretation of productivity variability through joint consideration of canopy condition and canopy structure.

6.4. Limitations of the dissertation

Although this dissertation demonstrates the value of multispectral, hyperspectral, and fused spectral-structural sensing for potato N assessment and yield prediction, its conclusions should be interpreted within the experimental and modelling context in which they were generated. The work was intentionally designed around selected sensing approaches, selected response variables, and

Manitoba field conditions rather than as a comprehensive assessment of all sensing platforms, crop traits, production environments, or decision systems. They should therefore not be extended uncritically to other potato-growing regions, cultivars, canopy forms, management systems, or stress environments. Agronomic variability associated with cultivar differences, seasonal conditions, crop developmental stage, and the presence of concurrent stresses may also modify canopy expression in ways that were not fully separated in this dissertation.

The temporal design of the empirical work also imposes an important boundary. The sensing chapters were organised around specific acquisition stages rather than dense multi-temporal monitoring across the season. This allowed comparison of sensing modalities at physiologically meaningful points, but it necessarily limited how completely the predictor space could represent traits that continued to evolve after sensing. That issue is especially relevant for tuber yield, which integrates later bulking, assimilate partitioning, canopy persistence, and late-season environmental responses that are only partly expressed at row closure. A single sensing stage can capture an important developmental moment, but it cannot fully represent the trajectory through which final productivity is formed. The yield-related findings should therefore be interpreted as in-season estimation from a restricted temporal window rather than as a full seasonal account of crop development.

Although PNN and final tuber yield were modelled jointly in Chapter 5, their direct relationship was not analysed because the study was designed to test whether both traits could benefit from shared sensor-derived information, rather than to use row-closure PNN as a predictor of yield. This remains an important limitation, and future work should quantify the potentially nonlinear, stage-specific relationship between PNN and yield using repeated PNN measurements while accounting for N treatment, year, and soil variability (e.g., soil texture and organic matter).

Another boundary lies in the mismatch between the observational scale of the predictors and the physiological scale of the reference variables. Petiole NO_3^- -N is a chemically specific tissue measurement, whereas the predictors used in the multispectral and fused chapters were derived primarily from canopy-scale optical and structural observations. The field component of the hyperspectral chapter was likewise based on canopy reflectance rather than direct spectral measurement of the exact tissue unit from which the reference variable was determined. This mismatch in observational scale does not invalidate the modelling approach, but it does place a natural ceiling on attainable correspondence. Canopy reflectance expresses the integrated effects of chlorophyll, canopy architecture, background, illumination, and within-plot heterogeneity, whereas petiole NO_3^- -N represents a narrower physiological compartment. In the multispectral chapter, this mismatch was further constrained by the UAV sensor configuration, which lacked a blue band and thereby restricted the set of VIs that could be evaluated. Part of the unexplained variance should therefore be understood not simply as model weakness, but as a consequence of linking related, though not identical, physiological and observational scales.

The empirical studies presented in Chapters 3–5 used PNN because it is sensitive to recent N uptake and aligns with routine in-season diagnosis in potato, whereas total tissue N represents the broader N pool accumulated in plant biomass. This choice limited the analysis to the mobile nitrate fraction; future studies should measure PNN alongside total N and the N nutrition index to determine which indicator is most consistently captured by canopy sensing and most closely related to crop response.

The hyperspectral results revealed a further limitation that is methodological as well as practical. Field canopy spectra, laboratory fresh-leaf spectra, and laboratory dried-powder spectra did not occupy the same predictive domain, even when they were used to estimate the same underlying

trait. Calibration transfer improved agreement between laboratory and field conditions, but it did not remove the difference between controlled and field-based measurements. This is important because it shows that spectral richness alone does not guarantee field robustness. In field environments, illumination variability, canopy shadowing, viewing geometry, leaf angle distribution, and background effects remain embedded in the sensed signal in ways that are difficult to standardize completely. As a result, part of the predictive strength observed under controlled conditions was necessarily attenuated when the model moved into the field domain. The dissertation therefore shows both the promise and the present boundary of hyperspectral sensing: it can strengthen N-related prediction, but its performance remains sensitive to the conditions under which spectra are acquired and transferred.

The behaviour of the models at the extremes of the response distribution marks another limitation. The parity plots, particularly those for the fused yield and PNN models, showed mild upper-tail compression, in which the highest observed values were not reproduced with equal spread in the predictions but instead were drawn into a narrower upper range. This points to reduced sensitivity where biological separation was hardest to preserve. Under dense potato canopies, optical predictors can lose discriminatory power as crop response approaches saturation, making it harder to resolve additional variation among highly vigorous plots. Statistical learning likely intensified that behaviour, because sparsely represented extremes are often drawn toward the centre of the fitted range when the predictor space does not provide strong separation at the tails. The result is not merely larger error at high values, but a more specific weakening of fine discrimination where crop status is most advanced.

The fused sensing framework in Chapter 5 should also be interpreted with restraint. The integration of LiDAR-derived structural metrics with multispectral variables broadened the representation of

canopy condition, but the added structural information did not produce a dramatic shift in overall prediction performance. That outcome is worth stating directly. Multi-sensor integration is often attractive because it promises complementary views of the crop, yet in practice its value depends on whether the added modality contributes information that is sufficiently distinct, stable, and well aligned with the trait being estimated. In this dissertation, structural information was informative, especially for yield interpretation, but its incremental gain remained moderate. The broader point is that fusion should not be treated as advantageous simply because more than one sensor is involved. Its usefulness depends on whether biological complementarity is actually preserved within the modelling framework rather than diluted within a larger predictor space.

Dataset size and composition impose another constraint on interpretation. As in many field-based sensing studies, the datasets were sufficient to support model development and independent testing, but still modest relative to the biological and environmental variability that governs crop behaviour across years and production settings. This matters particularly for deep learning, where model flexibility can exceed the diversity of the training domain and where performance may appear stable within the sampled environment while remaining sensitive to distributional shift outside it. The dissertation addressed this as carefully as possible through structured validation and separate test sets, yet the results should still be interpreted as evidence from bounded datasets rather than from fully heterogeneous production populations.

The final limit is operational rather than purely analytical. This dissertation was designed to evaluate selected sensing-based approaches, not to deliver a fertilizer recommendation system, an economic optimisation framework, or a complete commercial deployment pathway. Differences in flight height across acquisition campaigns may also have affected spatial detail and canopy representation, adding further variability to cross-dataset comparison. In other words, the

dissertation demonstrates research-grade predictive potential rather than fully operational readiness.

These limitations locate the contribution more precisely. The work provides evidence within the experimental and analytical space it was designed to examine, while leaving wider cross-context generalization for subsequent research.

6.5. Recommendations for future research

Future research in potato sensing should move beyond single-date sensing designs and adopt multi-temporal frameworks that follow crop development across key phenological stages. Recent N-monitoring literature shows that the value of RS depends strongly on growth stage and on whether observations are aligned with crop physiology and fertilization timing, rather than being confined to a narrow acquisition period (Y. Zhou et al., 2025). In potato, this suggests that future studies should test repeated-acquisition frameworks rather than expecting a single sensing stage to represent either end-of-season yield or the changing expression of crop N status across the season. The next step is therefore not simply to collect more imagery, but to construct temporally organised datasets that capture how canopy condition changes before, during, and after the period of strongest N responsiveness. Such designs would make it possible to distinguish transient canopy effects from developmentally persistent signals and to determine more clearly whether prediction improves through repeated observation or through better timing of fewer, more targeted acquisitions.

A second need is to develop models that are built for transfer rather than only for within-experiment accuracy. A recurring weakness in the literature is that relationships calibrated under one set of environmental conditions often lose strength when applied across years or regions. This limitation

has already been demonstrated in potato, where models based only on optical predictors showed limited interannual and regional stability, whereas transferability improved when environmental information was incorporated into the modelling framework (Y. Fan, Feng, et al., 2024). Future potato datasets should therefore be structured deliberately for transfer analysis, with repeated site-year combinations, broader environmental contrast, and stronger external validation across cultivars, soils, and management conditions. Beyond simple train-test separation, future work should treat transfer as a primary design objective. That will require intentionally heterogeneous datasets, more complete retention of acquisition and agronomic metadata, and direct testing of whether predictive relationships remain usable when moved across field environments rather than only within them.

A related priority is to broaden the predictor domain, but with much greater selectivity than is often seen in multimodal sensing studies. Future work should not proceed by simply accumulating variables. Instead, it should ask whether each added source contributes genuinely distinct information on canopy condition, field variability, or environmental constraint. Recent multimodal research suggests that fusion is most useful when different data sources contribute distinct information and when their relative importance can be adjusted according to context, particularly in sub-field prediction settings (Mena et al., 2025). For potato research, this points toward more deliberate integration of spectral, structural, meteorological, edaphic, and management variables in order to distinguish whether variation in N status or yield is being driven primarily by crop physiology, environmental forcing, or background heterogeneity. The most promising future studies will likely be those that move beyond simple feature concatenation and instead examine how each stream contributes under specific biological and management conditions. The next stage

of multimodal potato research is therefore not merely a matter of larger input space, but of better-organised information space.

Hyperspectral sensing deserves especially close attention in this regard, particularly as UAV hyperspectral systems become more technically mature and more accessible for field deployment. The main challenge is no longer the availability of richer spectra alone, but the development of more robust ways to manage spectral redundancy, noise, and signal variability. Recent methodological work has emphasized that feature extraction and feature selection are central to the success of hyperspectral applications because the dimensionality of the data can easily exceed the stability and interpretability of the useful signal if it is not carefully constrained (Xu et al., 2025). This means future studies should focus more directly on band selection, laboratory-to-field harmonisation, and domain adaptation strategies that reduce sensitivity to illumination effects, canopy geometry, shadowing, and background interference. An especially promising direction is the use of UAV-based hyperspectral imaging to bridge the gap between controlled spectroscopy and field-scale crop mapping. That would make it possible to test whether the biochemical specificity observed in laboratory or proximal measurements can be retained when hyperspectral information is acquired at operational spatial coverage. Such work would be valuable not only for N estimation, but also for determining whether hyperspectral imagery can separate nutritional stress from structurally induced optical variation more effectively than multispectral systems.

The relation between structural and spectral information also remains open for further refinement. In the present dissertation, structural metrics contributed useful but limited additional information. That outcome suggests that the next question is not simply whether fusion can be attempted, but under what biological and observational conditions it becomes informative. Recent reviews of crop N monitoring point in the same direction by showing that improved sensing performance will

depend not only on richer data sources, but also on better model transferability, stronger independent validation, and closer alignment between sensing strategy and agronomic purpose (Yu et al., 2025). Future studies should therefore test whether structural information becomes more valuable under denser temporal sampling, in more heterogeneous commercial fields, or when model architectures are designed to preserve modality-specific information. It would also be worthwhile to examine whether future fusion frameworks should be explicitly phenology-aware, so that the contribution of LiDAR, multispectral, and hyperspectral data can vary according to developmental stage rather than being treated as static inputs throughout the modelling process. That direction could lead to more biologically coherent sensing frameworks for potato yield formation and in-season crop diagnosis.

Model design itself is another area in which the next advances are likely to matter. Future potato sensing studies would benefit from shifting attention away from prediction alone and toward prediction with quantified uncertainty. In many agronomic settings, the practical question is not only what the predicted value is, but how confidently the model can separate strong from weak crop response under the available sensing conditions. This is especially relevant for N assessment under dense canopies and for yield estimation from limited in-season windows, where observational ambiguity is often part of the problem. Future work should therefore evaluate uncertainty-aware frameworks, confidence-calibrated predictions, and model comparison strategies that judge not only average performance but also stability across years, tails of the response range, and decision-relevant categories. For potato systems, that would provide a more useful basis for distinguishing where sensing products are robust enough to support management interpretation and where they should be treated more cautiously. This direction is also consistent

with the broader movement in crop RS toward models that are not only accurate, but also transparent about the limits of what the data can support.

Greater emphasis should also be placed on commercial-field complexity. Much of the strongest sensing work, including the present dissertation, necessarily relies on well-controlled experimental settings in which sources of variation can be separated more cleanly. The next stage of progress in potato research will require testing whether the same sensing logic remains informative under the irregularity of commercial production fields, where management history, soil variability, stand heterogeneity, disease pressure, irrigation patterns, and mixed stress interactions become harder to disentangle. Future studies should therefore examine larger commercial fields across multiple site-years and should test whether models trained under controlled experimental contrast remain interpretable when the crop is responding to several overlapping constraints at once. Scaling these relationships from research plots to UAV and satellite observations is important because it can extend locally calibrated information across entire fields and regions, providing the repeated spatial coverage needed for operational N management. This would create a stronger basis for evaluating whether the sensing variables that appear most informative in research plots retain the same biological meaning under production-scale variability. The movement toward this level of testing is already visible in recent potato and crop-yield studies using UAV hyperspectral and multispectral platforms in more heterogeneous operational settings.

The final direction concerns the place of prediction within agronomic decision support. Broader syntheses of crop prediction research suggest that progress will depend not only on improved predictive accuracy, but also on whether modelling frameworks are timely, interpretable, and usable for agricultural decision making in practice (Betew et al., 2025). For potato, this means that future studies should go beyond estimating petiole NO_3^- -N or yield and examine whether sensing

outputs can improve within-field sampling design, inform future variable-rate N strategies, identify low-response zones, and strengthen interpretation of yield variability under commercial conditions. The next stage of progress will therefore depend on making prediction more decision-relevant, not merely more technically sophisticated. In practical terms, this will require future studies to evaluate not only how well a model fits observed data, but whether its outputs can alter the quality of agronomic decisions at the time those decisions are still actionable. That shift from predictive performance alone to decision usefulness may ultimately be the point at which sensing research becomes more defensible as an agronomic tool rather than only as a predictive exercise.

6.6. General conclusions

This dissertation showed that remote and proximal sensing can strengthen potato N assessment and yield prediction under Manitoba field conditions, but their value was not the same across sensing approaches or prediction targets. Their usefulness depended on how well the sensing modality, acquisition conditions, and modelling framework matched the biological nature of the trait being estimated. Multispectral sensing was the most practical approach for in-season N assessment, hyperspectral sensing provided greater biochemical specificity when acquisition and calibration were carefully controlled, and fused spectral-structural modelling was more informative when the objective extended to integrative outcomes such as tuber yield. In sum, the dissertation provides a clearer basis for evaluating sensing-based approaches in potato systems and for guiding their more selective and biologically grounded use in future work.

6.7. References

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Appendices

Appendix A

Field and Acquisition Images

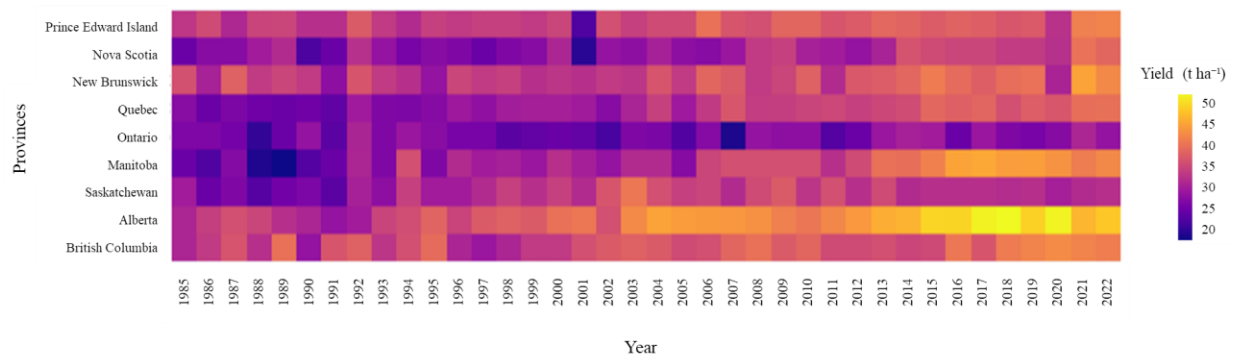


Appendix Figure A1. DJI Matrice 300 RTK UAV equipped with the Zenmuse L1 sensor prior to data acquisition in the experimental potato field; the RTK survey setup is visible in the background.

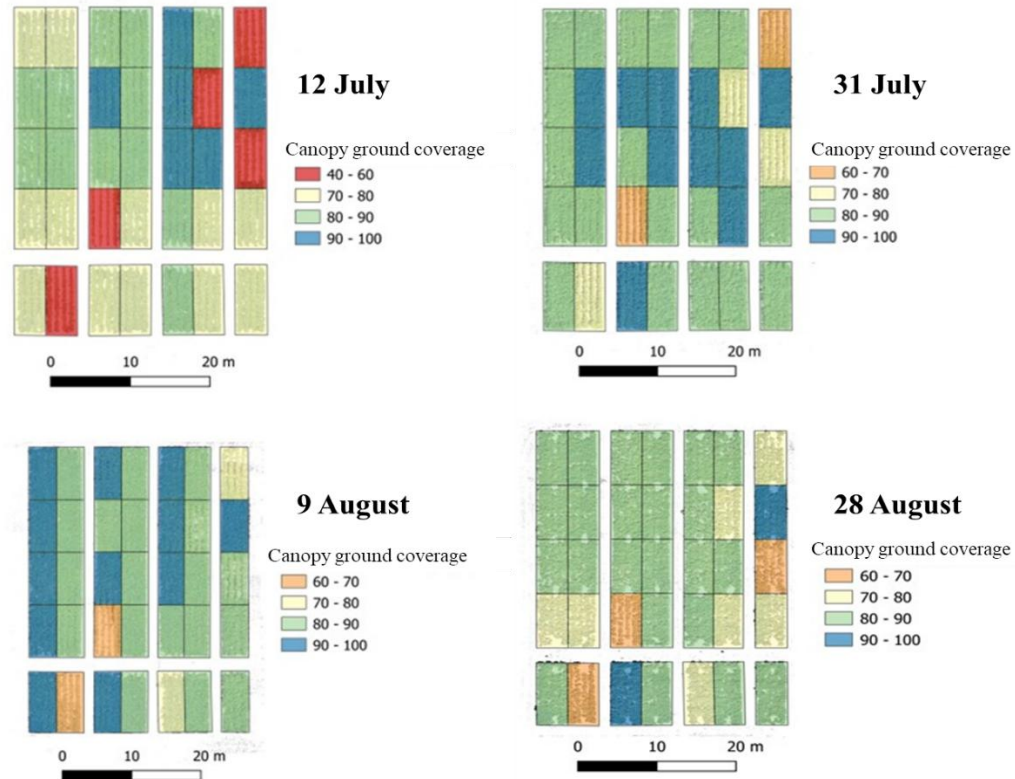


Appendix Figure A2. Aerial overview of the research site in Carberry, Manitoba, during the 2024 growing season, showing the spatial setting of the experimental potato plots examined in this dissertation.

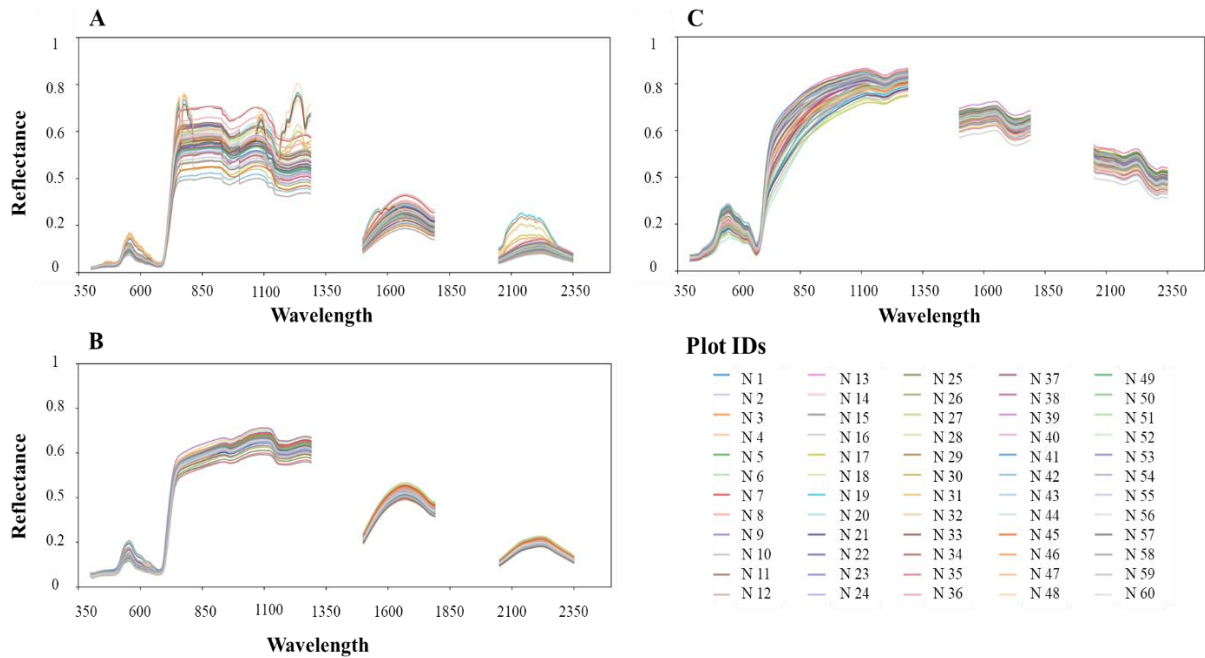
Appendix B
Supplementary Figures and Tables



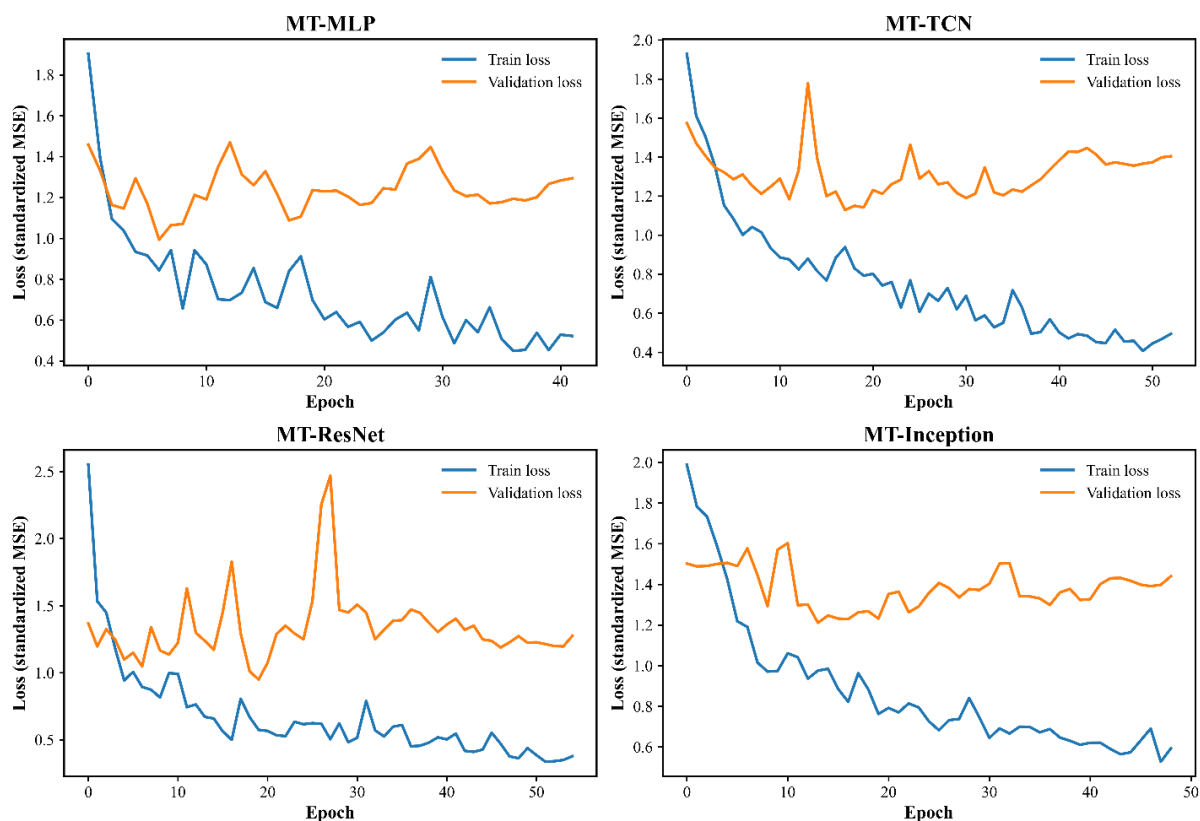
Appendix Figure B1. Provincial average potato yield in Canada from 1985 to 2022, shown as a heatmap in tonnes per hectare (t ha^{-1}). The figure summarizes long-term temporal and interprovincial variation in potato productivity across major Canadian producing regions and provides supplementary background for the national production context examined in Chapter 2. Source: Compiled by the author from Statistics Canada data.



Appendix Figure B2. Plot-level canopy ground coverage maps for the 2023 experimental potato field used in Chapter 3, derived from UAV orthomosaic imagery acquired on 12 July, 31 July, 9 August, and 28 August. Canopy coverage was estimated using the FIELDImageR workflow (Matias et al., 2020) and is presented as percentage classes for each acquisition date.



Appendix Figure B3. Raw hyperspectral reflectance signatures acquired over the 350–2500 nm range under three measurement conditions: (A) field canopy spectra, (B) laboratory fresh-leaf spectra, and (C) laboratory dried-powder spectra. Each curve represents the plot-level spectrum for one of the 60 sampled plots (N1–N60), showing the overall spectral structure and between-plot variability prior to preprocessing for the hyperspectral nitrogen modelling framework developed in Chapter 4. The 350–400 nm, 1290–1500 nm, 1790–2050 nm, and 2350–2500 nm regions were excluded from subsequent analysis.



Appendix Figure B4. Training and validation loss curves for the multi-task deep learning models used in Chapter 5. Loss is expressed as standardized mean squared error. In the multi-task setting, the plotted loss represents the combined optimisation objective for tuber yield and petiole NO_3^- -N prediction. For each architecture, the retained model corresponds to the epoch selected by early stopping on the basis of minimum validation loss. The figure provides supplementary evidence for model training behaviour and selection within the joint prediction framework.

Appendix Table B1. Sensitivity of multi-task model performance to fixed loss weighting. Test-set metrics are reported for tuber yield and petiole nitrate–N (PNN) across three values of the yield-loss weight (α).

Loss function: $L_{MT} = \alpha \text{MSE}_{\text{Yield}} + (1 - \alpha) \text{MSE}_{\text{PNN}}$

Architecture	Loss weighting		Yield prediction				PNN prediction			
	α_{Yield}	α_{PNN}	R ²	RMSE	MAE	RPD	R ²	RMSE	MAE	RPD
Inception	0.300	0.700	0.461	3.610	3.042	1.390	0.417	0.345	0.264	1.336
Inception	0.500	0.500	0.524	3.396	2.845	1.477	0.270	0.387	0.285	1.193
Inception	0.700	0.300	0.467	3.590	3.013	1.397	0.317	0.374	0.289	1.234
MLP	0.300	0.700	0.634	2.977	2.476	1.685	0.361	0.362	0.291	1.276
MLP	0.500	0.500	0.596	3.129	2.593	1.604	0.348	0.365	0.288	1.263
MLP	0.700	0.300	0.558	3.272	2.638	1.533	0.499	0.320	0.245	1.441
ResNet	0.300	0.700	0.347	3.975	3.200	1.262	0.547	0.304	0.246	1.515
ResNet	0.500	0.500	0.456	3.627	2.981	1.383	0.476	0.327	0.243	1.409
ResNet	0.700	0.300	0.489	3.517	2.946	1.426	0.346	0.366	0.260	1.261
TCN	0.300	0.700	0.493	3.502	2.951	1.432	0.578	0.294	0.234	1.570
TCN	0.500	0.500	0.499	3.483	2.813	1.441	0.641	0.271	0.217	1.703
TCN	0.700	0.300	0.469	3.586	2.877	1.399	0.535	0.309	0.252	1.495

Note. Bold values indicate the highest R² and lowest RMSE for each target within this sensitivity analysis.