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DIGITAL TRANSFORMATION IN CANADIAN CROP PRODUCTION: A SCOPING REVIEW OF EMERGING TECHNOLOGIES, TRENDS, AND POLICY GAPS

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Hanan Ishaque[1], V. Margarita Sanguinetti[12], Francine Nelson[1], Heather Ganshorn[3], Guillaume Lhermie[12]

1Simpson Centre for Food and Agricultural Policy, The School of Public Policy, University of Calgary, Calgary, Canada

2 Faculty of Veterinary Medicine, University of Calgary, Canada

3 Libraries and Cultural Resources, University of Calgary, Canada

Correspondence: guillaume.lhermie@ucalgary.ca

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ABSTRACT

This scoping review aims to systematically assess and synthesize current digital technologies and methodologies used in Canadian crop production research, including remote sensing, artificial intelligence (AI), the Internet of Things (IoT), robotics, and automation. The review examines how these technologies address key agricultural challenges, such as crop monitoring, pest management, irrigation, and soil health, while also exploring the perspectives of Canadian farmers, industry stakeholders, and policymakers on the opportunities, challenges, and ethical considerations associated with digital technology adoption in agriculture. The analysis centers on Canada's unique agricultural landscape, which combines ambitious sustainability goals with a sociopolitical framework that influences the innovation and integration of Digital Agricultural Technologies (DATs). As a significant food exporter, Canada faces region-specific barriers to DAT adoption, shaped by regulatory considerations, data governance, and privacy concerns. The review highlights that, while Canadian public sector-led research and innovation funding supports DAT development and testing, the widespread application of these technologies remains limited, with many still in experimental stages. By focusing on the technical and socio-technical dimensions, this review contextualizes DAT adoption as influenced by institutional, regulatory, and social factors unique to Canada, including emission reduction targets and data sovereignty. Using a sectoral innovation system framework, this study integrates technical data with social science perspectives to identify barriers and drivers impacting DAT diffusion in Canada, proposing a Responsible Research and Innovation (RRI) approach to address challenges. This nuanced analysis offers insights for policymakers and stakeholders, underscoring the need for continued research and cross-regional validation to support sustainable DAT integration. Notably, while findings are specific to Canada's crop production sector, they lay the groundwork for future policy directions and highlight gaps in international comparison that could inform Canada's approach to DAT development.

INTRODUCTION

The global population, currently at 8 billion as of 2022, is growing at an annual rate of 0.8% and is expected to reach 9.7 billion by 2050 (United Nations 2024). Food production will need to increase by 60-70% from current levels to meet the demand projected for 2050, driven by demographic and economic factors (Silva 2018). This will put a lot of pressure on global food production systems and exacerbate the environmental challenges. Canada is a leading agrifood producer and exporter, and with agriculture contributing 7% to its Gross Domestic Product (GDP), it ranks among the OECD countries with significant agricultural contributions (Windfeld and Lhermie 2022). It exports around 70% of its major crops and nearly 50% of its beef and cattle to the rest of the world and is well positioned to significantly contribute to global food supply (Canadian Chamber of Commerce 2024). However, the negative externalities of increasing food production limit the ability to do so in an environmentally sustainable manner. The agriculture sector in Canada accounts for 10% of the country’s total GHG emissions and contributes to broader ecological challenges (ECCC 2023). GHG emissions from the crop sector are mainly composed of Nitrous Oxide (N2O), about 97% of which comes from fertilizer use, including synthetic and organic applications, soil cultivation, and manure management. Emissions from animal production primarily result from cattle enteric fermentation and biomass decomposition, with approximately 90% as Methane (CH4) and 10% as N2O (Ishaque, Bourassa, and Lhermie 2024). Canada has set a target to achieve net zero emissions across all sectors by 2050 to meet its international commitment on climate change mitigation with specific reductions within agriculture playing a major role (ECCC 2020; GoC 2023). The agriculture sector faces the dual challenge of increasing food production to meet global demand while significantly reducing its climate footprint.

Digital agriculture technologies (DATs) have emerged as a powerful driver of this transition, advancing the capabilities of precision agriculture (PA) to make farming more efficient, sustainable, and data driven. DATs encompass an array of tools—such as big data analytics, cloud computing, IoT, and autonomous systems—that collect and process data to support precise, context-sensitive agricultural practices, improving both resource use and productivity (Agyemang and Kwofie 2021; Hailu 2023).

The International Society of Precision Agriculture (ISPA) defines PA as a management strategy that “gathers, processes and analyzes temporal, spatial and individual plant and animal data and combines it with other information” to support decisions that align with the natural variability in fields. By enabling such data-rich insights, DATs are central to achieving this objective, particularly in the face of global challenges like climate change, resource scarcity, and the need for resilient food systems (ISPA 2024). As the Fourth Industrial Revolution unfolds, these advanced technologies are reshaping agricultural practices, paving the way for more efficient, productive, and sustainable farming methods that also highlight the inequalities and unsustainable practices within the current food system (Agyemang & Kwofie, 2021; D’Odorico et al., 2019).

This transformative integration of DATs into PA represents a promising pathway to address the challenges in modern agriculture, though it also requires careful attention to social and institutional contexts to support wide-scale adoption and equitable access (McGrath et al. 2023) into farming practices is part of the broader movement known as Agriculture 4.0, also referred to as smart agriculture or digital agriculture (Abbasi, Martinez, and Ahmad 2022). DATs have enhanced the scope and functionality of precision agriculture (PA) by advancing data collection, storage, and processing capabilities beyond traditional methods focused on field variability and zone management. These technologies support applications ranging from basic mobile-based tools for technical support and farm monitoring to sophisticated systems using satellites and GPS for real-time weather prediction, field mapping, and variable rate application of inputs.

At the highest level, digital tools like specialized Farm Management Information Systems (FMIS) provide integrated platforms for managing various tasks, including crop rotation, animal handling, inventory, and financial management, allowing farmers to make more informed decisions from a centralized system (Abiri et al. 2023). This advanced connectivity and data-driven insight have made DATs essential not only for increasing productivity but also for promoting sustainability.

In modern agriculture, DATs are applied both horizontally across crop and livestock production and vertically along the entire food supply chain, encompassing everything from primary production to retail trade, insurance, and international trade. The primary production stage, essential to sustaining downstream industries (e.g., food processing, retail) as well as upstream inputs (e.g., seed production, fertilizers, veterinary services), benefits greatly from DATs to meet growing demands in a sustainable manner (Windfeld and Lhermie 2022). In Canada, 77% of primary agricultural output comes from crop production, fulfilling demands for food, animal feed, and biofuel feedstock, and making DATs vital in supporting productivity and sustainability across these sectors.

RATIONALE AND SIGNIFICANCE OF THE STUDY

The DATs include the use of existing technologies such as Landsat satellites which, since their launch in 1972, have enabled the monitoring of agricultural production across the globe, providing valuable data that contributing to informed decision-making in agriculture that supports productivity and land management (Wulder et al. 2022). Additionally, the implementation of satellite navigation through global positioning system (GPS) in the mid-1990s enabled automation of farm machinery, leading to more precise agricultural operations (precisions farming) and improved resource management (Lowenberg-Deboer and Erickson 2019). Some other technologies have also been used by Canadian farmers for a few decades such as yield monitors, autosteer, soil sampling using soil sample tests and variable rate technologies. However, the disruptive new innovations such as smart sensors, IoT, Cloud computing, big data analysis providing farmers with actionable insights to enhance decision-making. Artificial intelligence (AI) further expands these capabilities by analyzing vast datasets to identify patterns and predict outcomes, such as optimal irrigation schedules or pest outbreaks.

Research on digital agriculture often emphasizes the technical aspects involved in deploying these technologies to improve agricultural practices and productivity. However, digitalization of agriculture is a socio-technical process of applying digital innovations and goes beyond the development and validation of technologies (Klerkx and Leeuwis 2009). There also exists a body of literature that focuses on the economic, social, ethical, and institutional aspects of digitalization using various approaches (For example, (Bronson 2019; Duncan 2023; Murray Fulton et al. 2021; Phillips et al. 2019; Rotz et al. 2019; Soma and Nuckchady 2021;). This paper integrates natural and social science literature to review research on digital technologies in Canadian crop production over the past decade.

This review aims to (1) identify and critically assess the current digital technologies and methodologies applied within Canadian crop production research, including remote sensing, artificial intelligence (AI), the Internet of Things (IoT), robotics, and automation. Emphasis will be placed on evaluating how these technologies address significant agricultural challenges such as crop monitoring, pest management, irrigation, and soil health management; and (2) examine the perspectives of Canadian farmers, industry stakeholders, and policymakers on the opportunities, challenges, and ethical considerations surrounding the adoption and integration of digital technologies in crop production systems. This study centers on Canada's unique sociopolitical dynamics, agricultural practices, and innovation framework, which create specific pressures and opportunities in adopting digital agriculture technologies (DATs). As a major food exporter with ambitious sustainability goals, Canada faces regulatory challenges and adoption barriers that vary across regions. This country-specific focus enables a more accurate understanding of how DATs are tested, applied, and adopted, while also examining key social dimensions like data governance, privacy, and security concerns.

METHODOLOGY

This review follows the PRISMA-ScR framework ((Tricco et al. 2018; Page et al. 2021)) for scoping reviews.

Protocol and Registration:

A protocol was developed in line with PRISMA-P guidelines (Moher et al. 2015) and has been published in the Digital Repository of the University of Calgary (Sanguinetti et al. 2024) (Supplementary material 1).

Eligibility Criteria:

The eligibility criteria were specified for the population (P), intervention (I), comparators (C), outcome (O), and study design (S) (O'Connor et al. 2017). Within this review, three different types of primary research were identified. These were intervention studies where a DAT was tested in a main crop in Canada, uptake and qualitative studies, and policies identified from policy reviews. Not all the elements described will be relevant to all three types of primary research. The population of interest were the principal field crops during their growing stages i.e. plantation to harvesting (AAFC 2024). The interventions of interest included digital technologies farms could use to inform decision-making. Agricultural digital technologies refer to the multifaceted process that involves a) generating and collecting data using devices (e.g., sensors and satellites), b) integrating data to software platforms and statistical analysis (e.g., using Machine Learning), and c) providing output that facilitates the interpretation of results (e.g., a screen). Studies were retained where technologies assessed had at least one of the previous steps commercially available in Canada, and the assessment was conducted in Canada. Studies were required to have a concurrent comparison group (e.g. placebo or alternate assessment). For intervention studies, outcomes of interest included the intended use of the technology, statistical outcomes reported, and conclusions concerning which technology or statistical method used outperformed others. For uptake and qualitative studies, outcomes were adoption rates, motivators, and barriers to adoption. Randomized and non-randomized controlled trials and observational studies were included. Intervention studies were required to statistically assess the performance of digital technology. The full text had to be written in English and published in a peer-reviewed journal, thesis, or conference proceeding.

Database search:

The literature search covered multiple databases, including CAB Abstracts, BIOSIS, Web of Science, IEEE Xplore, and ProQuest Dissertations. The initial search was conducted on November 15, 2023, with an update on February 9, 2024. Search results were imported into Covidence (Veritas Health Innovation, Melbourne, Australia). Duplicated studies were removed automatically by the software and manually by the reviewers. Another review was used as a reference to confirm all relevant studies were being retrieved by the search strategy (Green, Fernandez, and MacPhail 2021). Additional studies were identified and included manually by the reviewers (Duncan 2018; Lemay et al. 2022 etc.) A librarian conducted the search strategy using controlled vocabulary and keywords related to DATs, limiting results to studies in English published from 2013 onwards. Detailed search strategies are provided in Supplementary materials 1 and 2.

Evaluation Process:

This review applies the sectoral innovation system (SIS) framework to analyze how various actors contribute to developing, producing, and adopting digital agricultural technologies (DATs). Within this framework, farmers, advisors, technology designers, and policymakers are positioned not only as end-users but also as co-developers, contributing insights that shape the technology lifecycle. Our evaluation process was structured in two stages, ensuring that each reviewer fully understood the inclusion and exclusion criteria for identifying relevant studies (Dohoo, Martin, and Stryhn 2009; O'Connor et al. 2017; Sargeant and O'Connor 2020).

During the initial screening, titles and abstracts of studies were reviewed with guidance from signalling questions, and studies were classified for inclusion or exclusion. Conflicts were resolved through discussion between reviewers, with a third reviewer consulted if needed. In the second stage, full texts of studies were screened based on the SIS approach, categorizing each study by its contributions to different stages in the innovation process, such as validation, production, and adoption (Malerba 2002). Data extracted included study identifiers (author, year, funding, location) and, where relevant, specific details of DATs such as intended use, target crops, data collection and analysis methods, and the stakeholder dynamics that influenced outcomes.

Synthesis of results:

To synthesize results effectively, we categorized studies based on their focus within the DAT innovation continuum (Busse et al. 2014a). Technical studies, aligning with the validation phase, were organized by technology type, crop type, data collection technology, and analysis methods. Summaries of findings for these studies were compiled, and matrices were created for cases with more than two studies, allowing us to identify trends across similar crop types, data collection approaches, and statistical outcomes (Green, Fernandez, and MacPhail 2021).

Qualitative studies were grouped by stakeholder perspectives, which enabled a comparative analysis of factors affecting DAT adoption. For each stakeholder group, personal, interpersonal, and contextual determinants were analyzed and compared (Bronson and Knezevic 2019). This process helped to map the social dimensions within the production and adoption phases of DAT innovation, capturing how social and institutional dynamics influence technology uptake beyond the farm level.

Analytical Framework:

This review employs the sectoral innovation system (SIS) framework to examine the development, production, and adoption of digital agricultural technologies (DATs) in Canadian crop production. In this system, various actors—such as scientists, entrepreneurs, and farmers—collaborate within a shared knowledge environment to address sector-specific challenges (Bergek et al. 2008; Malerba 2002). The innovation process is viewed in three phases (Busse et al. 2014a):

Validation: Technical studies in this review highlight recent advancements in DATs and prototype testing, representing the knowledge creation essential for early-stage innovation.

Production: This phase includes scaling from prototypes to market-ready products, requiring collaboration among developers, manufacturers, and regulators. Insights from international literature guide the analysis of factors critical for successful DAT commercialization.

Adoption: Adoption, shaped by broader institutional and policy dynamics, involves farmers not only as users but also as co-developers whose feedback refines DATs to align with practical needs (Bronson 2019).

The SIS framework thus provides a structured view of the full DAT lifecycle, encompassing technology creation, scaling, and the systemic factors influencing adoption. Figure X illustrates these phases and actor roles.

RESULTS

The search strategy found 1283 relevant studies, of which 248 duplicates were removed. One thousand and thirty-five studies underwent title and abstract screening, and 818 were excluded during this stage. Two hundred and seventeen studies underwent full-text screening, and 83 were included in the narrative review Figure 1.

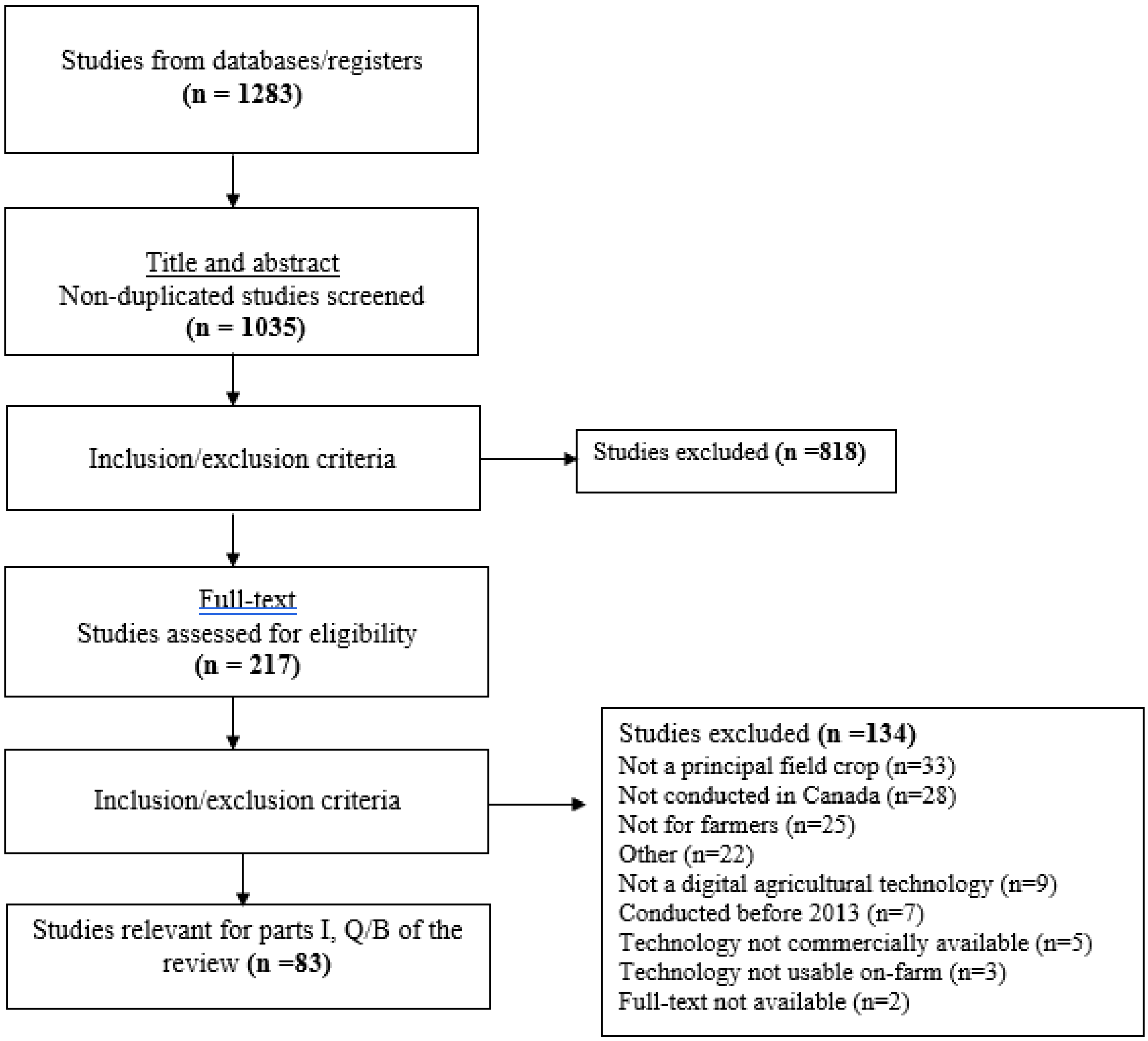

Figure 1 Prisma flowchart of the scoping review in a scoping review of agricultural digital technologies developed and assessed in main crops and barriers and motivators of different stakeholders for their adoption in Canada.

STRUCTURED REVIEW OF TECHNOLOGIES AND STAKEHOLDER INSIGHTS

The technical studies predominantly focused on the validation stage, encompassing research, prototyping, and experimental testing of DATs in Canadian crop production (Busse et al. 2014a). These studies demonstrated the feasibility of various DAT applications, detailed crop-specific data collection methods, and assessed different analytical techniques, providing foundational knowledge for DAT development.

In contrast, the qualitative studies explored the production and adoption stages, analyzing stakeholder perspectives to uncover factors shaping DAT market dynamics, user experiences, and broader institutional influences on adoption (Bronson 2019; Klerkx, Jakku, and Labarthe 2019). These studies underscored the importance of system-level support and engagement with a variety of stakeholders, as adoption is affected by both the broader social context and direct farm-level applications (Higgins et al. 2017; Malerba 2002).

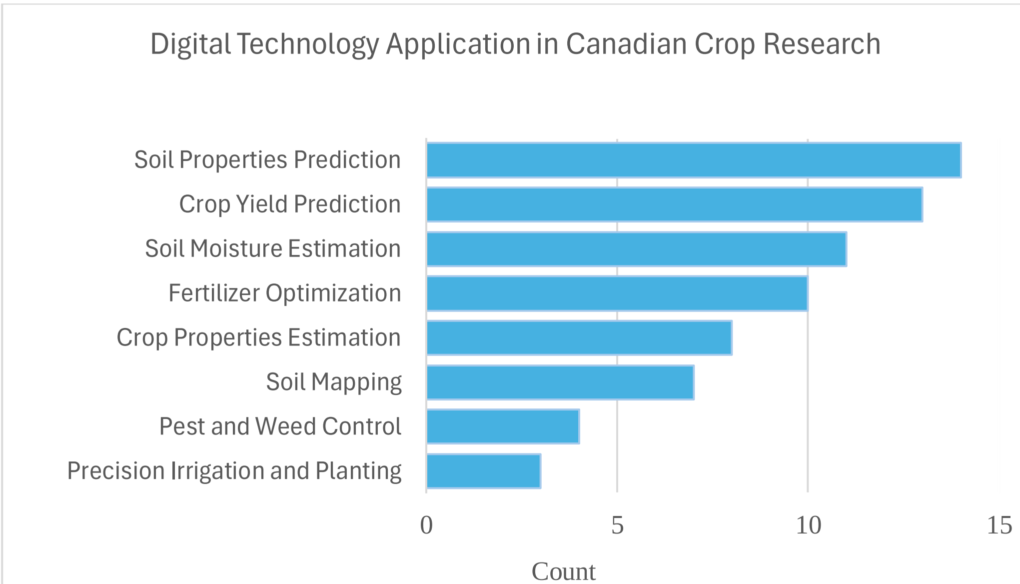

Figure 2 Distribution of Reviewed Studies by Digital Technology Application in Canadian Crop Research.

The studies reviewed on DAT implementation in Canadian crop production were categorized according to specific application areas, providing a clear view of their distribution across soil and crop management needs. These categories included Soil Properties Prediction, Soil Mapping, Soil Moisture Estimation, Crop Properties Prediction, Crop Yield Prediction, Fertilizer Optimization, Precision Irrigation and Planting, and Pest and Weed Control (Figure 2). This distribution highlights the diverse applications of DATs, with soil and crop-focused technologies addressing fundamental agricultural needs for improved productivity, resource efficiency, and environmental sustainability. Most of the technical studies included in this review were conducted in Ontario. A substantial number of studies have also been done in Manitoba. A detailed distribution of the number of studies conducted in each province are shown in Figure 3.

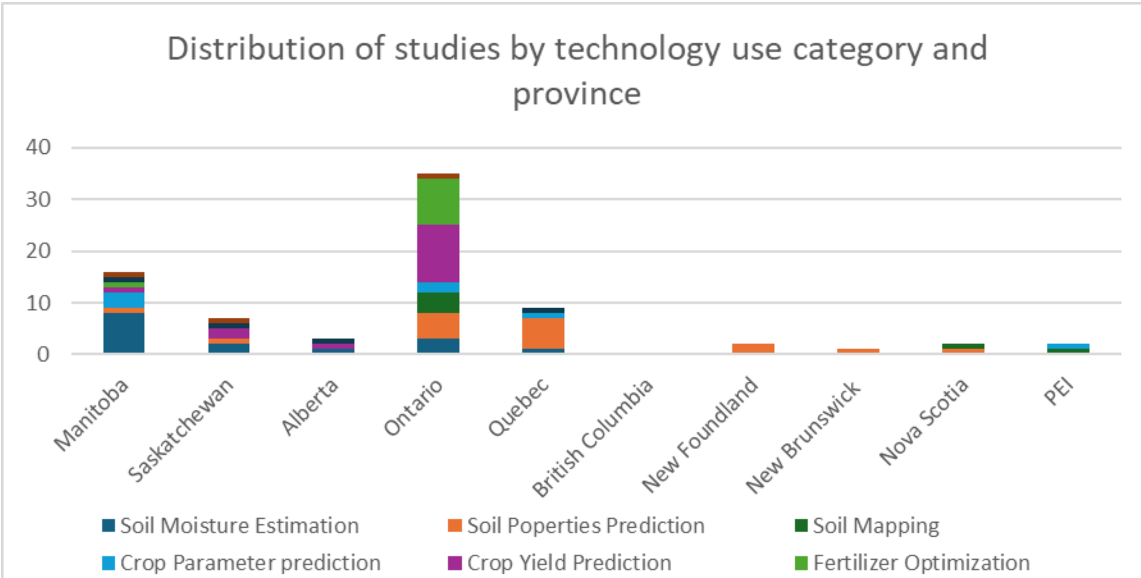

Figure 3 Provincial Distribution of DAT Studies by Technology Application Category in Canadian Crop Production

DAT APPLICATIONS IN CROP PRODUCTION

Soil Properties Estimation:

The estimation of physical, chemical, and biological soil attributes—such as texture, organic matter, nutrient content, pH, soil electrical conductivity, and cation exchange capacity—is essential for effective zone delineation and management. Traditionally, soil assessment has relied on labor-intensive surveys and lab analyses. However, advancements in sensor technology have enabled the mapping of soil heterogeneity more efficiently. These sensors produce signals that correlate with specific soil properties, either through remote or proximal sensing systems (PSS), depending on their distance from the soil (Nandkishor Motiram Dhawale 2015). Compared to traditional methods, PSS technologies allow for high-volume data collection with lower labor demands (Huang 2007).

Active PSS systems, such as ground-penetrating radar (GPR) for soil water content and electromagnetic induction (EMI) for soil electrical conductivity, introduce energy into the soil to measure responses. Passive systems, like near-infrared and ultraviolet-visible-near-infrared (vis-NIR) spectrometers, measure natural gamma-ray radiation for soil composition analysis. Table 1 categorizes proximal soil sensing (PSS) technologies by their operation type—active or passive sensing—and by their mode of soil contact, distinguishing between contact-based and non-contact methods. This classification highlights the diversity in PSS approaches tailored for different soil properties and field conditions. Direct PSS techniques measure soil properties using in-situ analyzers. Most PSS systems operate as on-the-go sensors, using Real-Time Kinematic (RTK) GNSS to create georeferenced surface maps that inform management practices (Md Saifuzzaman 2020). For example, (Adamchuk and Dhawale 2014) introduced an on-the-spot soil analyzer (OSA) capable of deploying multiple sensors simultaneously on all-terrain vehicles, capturing data at specified depths.

Table 1 Categorization of PSS Technologies Based on Operation Type and Soil Contact

Sensor Type	**Active/Passive**	**Direct/Indirect**
Ground Penetrating Radar (GPR)	Active	Direct
Electromagnetic Induction (EMI)	Active	Direct
Gamma Ray Spectroscopy	Passive	Direct
Near Infrared (NIR)	Passive	Indirect
Mid Infrared	Passive	Indirect
Ultraviolet–Visible–Near–Infrared (vis-NIR) Spectrometers	Passive	Indirect
Ground-penetrating radar (GPR) (using radio and microwaves)	Active	Indirect

Source: (Huang 2017; Rossel et al. 2011)

Calibration models are then validated with independent datasets, ensuring reliable soil property estimates. The predictive performance of these models varies depending on the soil properties, agronomic conditions, and dataset size. For example, found that partial least squares regression outperformed simple linear regression when predicting soil organic matter and texture using vis-NIR sensors. Additionally, Dhawale et al. (2022) showed that mid-NIR spectrophotometers predicted sand content more accurately than portable mid-IR sensors, while vis-NIR spectrophotometers better estimated clay content.

Of the fourteen studies reviewed, twelve used PSS techniques, including EMI, mid-IR, and gamma-ray spectrophotometers, to predict physical soil properties like moisture, texture, CEC, and pH (Altdorff et al. 2020; Badewa et al. 2019; N M Dhawale et al. 2022; Ji WenJun et al. 2019; Laamrani et al. 2019; M Saifuzzaman et al. 2021). Taneja et al. (2021) used cell phone images to estimate soil moisture and nitrogen levels. Two studies in this category used remotely sensed data for soil characterization and nutrient detection: Bouroubi et al. (2014) used multispectral imagery using Worldview- 2 satellite and (Wrozyna 2020) used UAV mounted sensors. Calibration methods across these studies included machine learning, regression, and simulation models (Table 2).

Table 2 Summary of Studies on Soil Properties Estimation: Crop Types, Data Collection Techniques, and Data Analysis Methods

Soil properties (n=14)	Crops			Data collection		Data analysis			
	Corn	Soybean	Wheat	Remote sensing (Satellites and RADAR)	Proximal and in-situ sensing (cellphone camera, electromagnetic induction, portable sensors, OSA, UAV)	Machine Learning	Regression methods	DSSAT Simulation	Other
	9	5	3	2	12	3	4	2	5

Thematic Soil Mapping:

The call for site-specific management (SSM) through variable-rate nitrogen (N) applications has increased in recent years among government agencies and farming communities. SSM typically operates within management zones, or field sub-areas exhibiting uniform soil, crop, or yield characteristics (Dong et al. 2019). High-density sensor measurements, combined with spatio-temporal data, provide a detailed understanding of soil variability that enables accurate SSM (Hengl et al. 2018).

Proximal and remote sensing technologies help delineate homogeneous field zones by mapping field heterogeneity and environmental variables, creating thematic soil maps. Digital soil mapping (DSM) correlates environmental data from remote and geospatial sources with machine learning models to predict soil properties. This method produces thematic maps, like those for soil organic carbon, moisture, and nutrients, which support precision agriculture, environmental management, and land-use planning.

This review examined seven studies focused on thematic map applications (Altdorff et al. 2020; Dong et al. 2019; Huang 2017; H. Lee, Wang, and Leblon 2020; Paul, Heung, and Lynch 2022; Md Saifuzzaman 2020; Vlachopoulos et al. 2022). Thematic maps were created for various agricultural needs, including nitrogen optimization, soil property mapping, field variability analysis, and crop health assessment. Three studies used remote sensing devices, including Landsat data (Paul, Heung, and Lynch 2022), UAVs with multispectral sensors (H. Lee, Wang, and Leblon 2020; Vlachopoulos et al. 2022), and RapidEye satellite data (Dong et al. 2019). Altdorff et al. (2020) evaluated electromagnetic induction sensors for mapping soil properties, while (Huang 2017) used multi-sensor soil maps compared with satellite imagery and regression-based calibration models. Table 3 summarizes the thematic map applications explored across the reviewed studies.

Table 3 Summary of Studies on Soil Properties Estimation: Crop Types, Data Collection Techniques, and Data Analysis Methods

Thematic mapping (n=7)	Crops				Data collection		Data analysis**	
	Canola	Corn	Soybean	Wheat & Barley	Remote sensing (Satellite, LiDAR)	Proximal sensing (e.g., EMI and Portable Sensors)	Machine Learning	Regression/other algorithms
	1	4	2	2	4	3	5	3

Soil Moisture Estimation:

Soil moisture (SM) is a key factor in agricultural productivity, affecting crop yields and influencing the occurrence of natural disasters such as droughts and floods. Its high spatial and temporal variability makes large-scale measurement challenging, particularly through in situ monitoring networks (Li JunHua and Wang ShuSen 2018). Traditional in situ methods, like time-domain reflectometry (TDR) and Stevens HydraProbe sensors, can measure SM accurately but are too costly for widespread spatial application (S. J. Lee et al. 2023). Satellite-based sensors and techniques have been widely employed for SM estimation, especially through microwave remote sensing, which has been effective over the past two decades (Calvet et al. 2011; Ulaby, Moore, and Fung 1981). Microwave sensors include active types, with both transmitter and receiver elements (e.g., radars), and passive types, which only have receivers (e.g., microwave radiometers) (Ulaby, Moore, and Fung 1981). Satellites such as Sentinel-1 utilize C-band SAR to capture radar backscatter changes that correlate with SM levels, while L-band instruments like SMOS, AQUARIUS, and SMAP monitor SM and ocean salinity (Abbes, Magagi, and Goita 2019; Champagne et al. 2016). Combining SAR, passive radiometry, and optical sensors provides a comprehensive SM monitoring approach across varying conditions and scales.

This review identified several studies using remote sensing technologies to estimate SM, including UAVSAR, SMOS, RADARSAT-2, and Sentinel-1 and 2 (Abbes, Magagi, and Goita 2019; Akhavan et al. 2021; Champagne et al. 2016). Machine learning (ML) methods were commonly applied to analyze remotely sensed data, given their usefulness in capturing complex, non-linear data behavior (Ali et al. 2015). Table 4 presents a summary of the findings within this category of studies.

Table 4 Summary of Studies on Thematic Soil Mapping: Crop Types, Data Collection Techniques, and Data Analysis Methods

	Crops					Data collection		Data analysis			
Soil moisture estimation (n=11)	Canola	Corn	Soybean	Wheat	Others	Remote sensing (Satellites and RADAR, L-Band radiometer)	In situ and proximal sensing (cellphone camera, in situ and portable sensors)	Machine Learning	WCM-Ulaby	Others (Regression, stability analysis, etc)	DSSAT Simulation
	7	7	8	4	7	9	2	5	2	3	1

Crop Properties Prediction:

Remote sensing technologies, especially multispectral and hyperspectral Earth observation (EO) imaging, are used in precision agriculture to capture spatial variability in plant growth. These methods enable early detection of crop needs such as fertilizer, irrigation, and pest control by analyzing vegetation indices like the Normalized Difference Vegetation Index (NDVI), which estimates parameters such as Leaf Area Index (LAI) and biomass (Bourassa and Vinco 2022). Various methods of high-resolution imagery collection—UAV imagery, satellite, and aerial photography—allow detailed monitoring at different scales.

In this review, eight studies estimated crop parameters using remote sensing technologies. UAV multispectral imagery, for example, was used by (H. Lee, Wang, and Leblon 2020) and Song et al. (2016) to predict canopy nitrogen weight, while Vlachopoulos et al. (2022) estimated the green area index for mapping crop health. These studies applied machine learning and multiple linear regression models to predict crop parameters, indicating growing reliance on advanced analytics. Hosseini et al. (2015) showed that C and L band Synthetic Aperture Radar (SAR) sensors reliably monitored crop productivity regardless of weather conditions by using the Water Cloud Model-Ulaby (WCM-Ulaby) model. Additionally, studies highlighted that SAR polarimetric integration H. Lee, Wang, and Leblon (2020) with spectral vegetation indices could improve dry biomass and LAI estimation (Bahrami et al. 2021). Table 5 presents a summary of the findings within this category of studies.

Table 5 Summary of Studies on Crop Properties Estimation: Crop Types, Data Collection Techniques, and Data Analysis Methods

	Crops			Data collection		Data analysis			
Crop parameters estimation (n=8)	Corn	Soybean	Wheat	Remote sensing (Satellites and RADAR, UAVs)	Proximal and in-situ sensing (Ground penetration Radars, Portable sensors and cameras)	Machine Learning	Water Cloud (WCM)-Ulaby	DSSAT Simulation	Other
	6	4	2	05	03	3	2	2	1

Crop Yield Prediction:

The within-field variability of soil properties is directly related to spatial and temporal differences in crop productivity, growth, and yield (Dong et al. 2019). Ground-based sensing methods, such as electrical conductivity, provide useful soil property information for zone delineation but lack economic viability on a large scale. Remote sensing presents a more efficient option, enabling soil and crop data collection over vast areas. Advances in high-resolution optical sensors like RapidEye and Sentinel-2, which feature frequent revisit cycles, allow for fine-scale detection of spatial patterns in soil properties, crop growth, and productivity and can even aid in yield prediction (Jing et al. 2016).

The studies reviewed used both proximal and remote sensing technologies to predict crop yields in Canadian soils, collecting data through hand-held imaging devices (Bi et al. 2023), yield sensors on combines with GNSS receivers (Burdett and Wellen 2022; Capmourteres et al. 2018), topographic LiDAR data (Eyre et al. 2021), satellite imagery ((Dong et al. 2019; Gogoi et al. 2023; Liao et al. 2023a), and UAVs (Killeen et al. 2024; Song and Wang 2016). Vegetation indices derived from satellite data, such as NDVI, EVI, EVI2, MTVI2, WDRVI, and NDWI, were extensively utilized for yield prediction (Liao et al. 2023a). These indices have proven effective for forecasting yield and informing stakeholders like producers and policymakers (Killeen et al. 2024).

Another subset of studies employed agroecosystem simulation models to simulate crop growth and dynamics of soil carbon, water, and nitrogen in agricultural systems. The DSSAT v4.6 model, for instance, was used to simulate spring canola with the CSM-CROPGRO-Canola model (Jing et al., 2016), while the DSSAT-CSM and DSSAT-CERES models simulated wheat and maize responses to various inputs (Li et al. 2015; Liao et al. 2023b; Liu et al. 2021). These models vary in their approaches to simulating crop and soil processes, depending on specific data and parameters. Table 7 presents an overall summary while Table 6 provides a detailed summary of the studies on yield prediction included in the review.

Table 6 Summary of Studies on Crop Yield Prediction: Crop Types, Data Collection Techniques, and Data Analysis Methods

	Crops			Data collection		Data analysis				
Yield Prediction (n=13)	Corn	Soybean	Wheat	Remote sensing (Satellites and RADAR, UAVs)	Proximal and in-situ sensing (ViT transformer, portable sensors, yield monitors)	Machine Learning	Regression methods	DSSAT Simulation	Other	Water Cloud (WCM)-Ulaby
	6	4	6	06	1+6	3	2	6	3	1

Table 7 Summary of Yield Prediction Studies

Author(s)	Year	Data Type	Method Type	Approach
Bi et. al.	2023	Images captured using handheld device	Remote sensing	Image segmentation and deep-web method CNN-LSTM
Burdet and Wellen	2022	Harvest Yield Monitor	Ground measurements	Multiple linear regression, Artificial Neural Networks, Random forests, and decision trees
Capmourteres et. al.	2018	Harvest Yield Monitor	Ground measurements	Profit map using a Kriging interpolation
Dong et. al.	2019	Satellite Imagery	Remote sensing	ANOVA with Tukey–Kramer test Fuzzy C-mean Clustering (FCM) algorithm
Eyre et. al.	2021	LiDAR surface data	Proximal sensing	Geographic weighted regression (GWR) technique
Gogoi et. al.	2023	Satellite Imagery	Remote sensing	Linear regression model
Herath et. al.	2017	Soil Sampling	Ground measurements	Pearson's correlation
Jing et. al.	2016	Field experiments	Ground measurements	DSSAT-GROPGRO simulation model
Killeen et. al.	2022	UAV imagery	Remote sensing	Random Forest model and Linear Regression

Liao ChunHua	2022	Satellite Imagery	Remote sensing	Multivariate linear regression (ML) and three simple unsupervised domain adaptation (DA, ML) methods
Liu	2021	Field experiments	Ground measurements	DSSAT-CERES Simulation
Li ZhuoTing	2015	Field experiments	Ground measurements	DSSAT-CSM Simulation
Liu	2014	Field experiments	Ground measurements	DSSAT-CSM Simulation
Song	2020	UAV imagery	Remote sensing	Point Cloud Method and simple algorithm for yield estimation (SAFY)

Fertilization Optimization:

Farmers require decision support to address spatial heterogeneity within fields for site-specific nitrogen fertilization and N management practices. Given that fertilization significantly contributes to agricultural expenses, optimizing fertilizer efficiency can substantially reduce costs. This involves considering soil factors (e.g., water, tillage), fertilization techniques (e.g., variable rates, application methods), and crop-specific needs (Shinde 2017). Ten studies in this review focused on improving nitrogen (N) management in agriculture using digital technologies and through diverse methods tailored to specific goals. Some studies aimed to determine the effectiveness of variable rate N application in reducing N2O emissions and enhancing yield in no-till canola production (Glenn et al. 2021). The other studies evaluated decision support systems like DSSAT for simulating crop responses to N application and soil water storage or compared variable- and uniform-rate N strategies in maize to assess their impact on yield and soil nitrogen (Liu et al. 2021; Shinde 2017). Additionally, certain studies developed machine learning models and UAV-based tools to predict canopy nitrogen levels and optimize site-specific N recommendations ((Ma, Wu, and Shang 2014; Song and Wang 2016; Yu, Wang, and Leblon 2021). Collectively, these studies sought to enhance precision in N management to boost yields, improve economic outcomes, and reduce environmental impacts. Table 8 presents a summary of the studies on fertilizer optimization.

Table 8 Summary of Studies on Crop Yield Prediction: Crop Types, Data Collection Techniques, and Data Analysis Methods

	Crops				Data collection				
Fertilizer Optimization (n=10)	Corn	Canola	Wheat	Soybean	Remote sensing (Satellites and RADAR, UAVs)	Proximal and in-situ sensing (Ground penetration Radars, Portable sensors and cameras)	Machine Learning	DSSAT Simulation	Other
	4	2	2	2	02	08	3	2	5

Pest and Weed Control:

Four studies assessed digital technologies intended to tailor the use of pesticides and herbicides in crops (Das 2021; Stanhope 2016; Truong, Dinh, and Wahid 2017; Zhang ChunHua, Walters, and Kovacs 2014) (Table 9). Within the three, data was gathered using cameras mounted to a quad (Das 2021), farm equipment (Stanhope 2016), IoT sensors (Truong, Dinh, and Wahid 2017); and near-IR camera mounted on a UAV (Zhang ChunHua, Walters, and Kovacs 2014). Methods to analyze data included deep learning and machine learning methods (Das 2021; Truong, Dinh, and Wahid 2017), NDVI-derived maps (Zhang ChunHua, Walters, and Kovacs 2014), and other algorithms developed with Python (Stanhope 2016).

Table 9 Summary of Studies on Pest and Weed Control: Crop Types, Data Collection Techniques, and Data Analysis Methods

	Crops			Data collection		Data analysis	
Pest and Weed Control (n=4)	Corn	Soybean	Canola	Remote sensing (Satellites and RADAR, UAVs)	Proximal and in-situ sensing (Cameras, vehicle mounted sensors, IoT sensors)	Machine/ Deep Learning	Image Processing
	1	2	1	01	03	2	2

Precision planting and Irrigation:

There are three studies in this category. Françis and Laforest (2015) developed a smart tractor system for PA, designed for smaller farms. It included variable rate control for tractor speed based on sensor inputs and an automated planting system adjusting depth using a soil moisture sensor. Post-emergence crop vigor was assessed with aerial imagery and a Greenness Excess Index (GEI). The results highlighted that inconsistent speed response and varying planting depths impacted crop performance, with 5.0 cm emerging as the optimal planting depth in different moisture conditions. However, findings on the ideal depth in wet and dry soils were inconsistent. Dhillon et al. (2022) compared precision planting with a vacuum planter and conventional air drill for canola in southern Alberta. In some cases, there was no significant yield difference. Sadri et al. (2022) focused on developing a machine learning algorithm (Random Forest) to forecast irrigation needs for crops like canola and spring wheat.

Analysis of Funding Sources for Crop Production Research in Canada:

Federal funding is the predominant source across most provinces, particularly in Ontario and Quebec, reflecting strong federal support for agricultural research. Provincial agencies also play a significant role, especially in Quebec and Manitoba, while producer groups contribute minimally, seen only in a few provinces. Additionally, a category labeled "Other" appears across several provinces, suggesting alternative funding sources beyond federal, provincial, and producer group contributions. This distribution highlights the regional differences in funding structures and the importance of diverse funding sources in advancing agricultural research. Figure 4 illustrates the distribution of funding sources by province for crop production research studies in Canada.

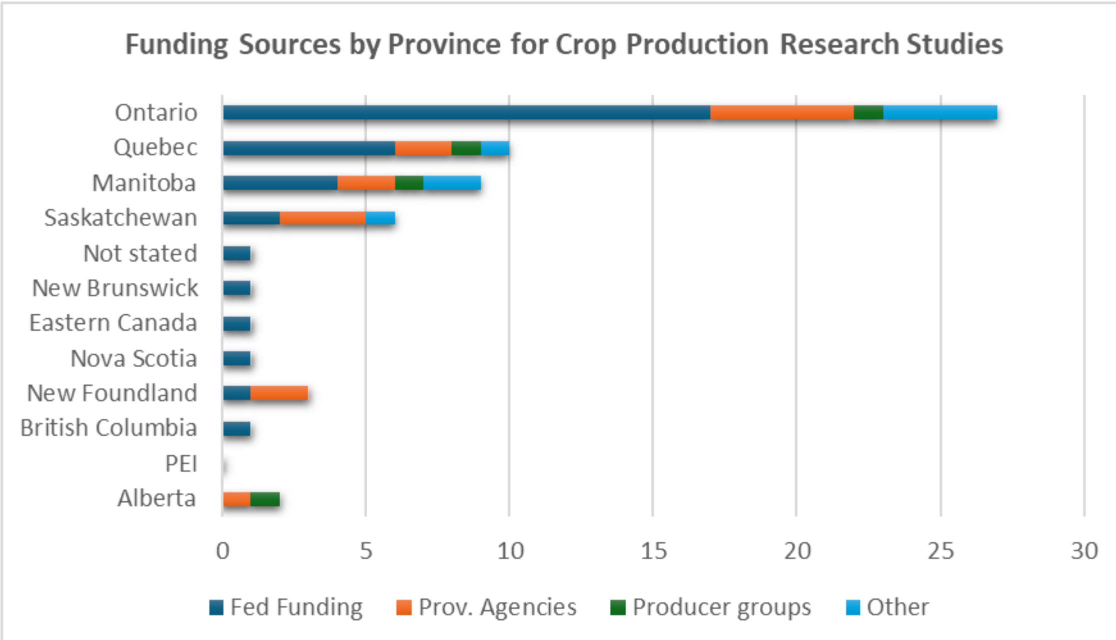

Figure 4 Funding Sources by Province for Crop Production Research Studies

DIGITAL TECHNOLOGY PRODUCTION AND ADOPTION

The review of technical research studies highlights the recent developments in both fundamental and applied research on digital agricultural technologies (DATs), as well as the experimental testing of prototypes and analytical methods for diverse applications in Canadian crop production. This represents knowledge creation and cutting-edge research that has the potential to be commercialized. This phase of the innovation process can be termed as 'validation' phase of the three-phase continuum defined by Busse et al. (2014). To study the 'production' and 'adoption' phases of the process, it is necessary to explore the interplay of the innovation system components and the outcomes of innovation activities (Busse et al. 2014). The second set of studies in this scoping review present the qualitative research on digital agriculture in the last decade. These include studies on DAT adoption which take a dynamic system perspective suggesting that technological advancements are influenced by complex institutional factors operating at multiple levels beyond the farm itself (Bronson 2019). The 'production' phase comprises mass production and market launch and there is extensive international literature that explores various types of innovation systems, analyzing their characteristics and assessing their performance (see. (Higgins et al. 2017; Klerkx and Leeuwis 2009; Malerba 2002). Although there are very few studies conducted in Canada that provide an analysis on production stage of the innovation process, this review presents the positive and normative dimensions of stakeholder inclusion during the technology design phase of production of DATs. For example, Bronson (2019; Ebrahimi, Sandra Schillo, and Bronson 2021) explore the impact of decisions made by scientists and designers at the design stage of DAT development which maybe responsible for uneven adoption at a much later stage.

The research that explores the 'adoption' phase of the innovation process discuss three broad topics: the dynamics of DAT adoption in Canada; challenges associated process of change with DATs; and frameworks aimed at addressing these challenges. These studies take two types of approaches: political economy framework and constructivist approaches from science and technology studies (STS). The former analyzes the role of DATs in shaping power relations, market dynamics and structures (see, for example, (Bronson and Knezevic 2016; 2019; Duncan 2018; Phillips et al. 2019; Rotz, Duncan, et al. 2019). The STS framework focuses on how various socio-cultural factors shape the development of DATs. This framework explores the discourse surrounding DATs and how they are understood by different actors, affecting the adoption (for example, (Duncan et al. 2021; Soma and Nuckchady 2021). Adoption rates, factors, barriers, and implications of DATs can be analyzed using both political economy and Science and Technology Studies (STS) frameworks. While political economy focuses on how economic structures and power dynamics shape adoption, the STS examines the social and cultural contexts influencing technology development and use. Together, these approaches provide a holistic understanding of the forces driving DAT adoption, from institutional power to social practices.

Variability in DAT Adoption Rates:

Technology adoption rates in Canada and associated factors have been explored only recently and the Canadian Census of Agriculture (COA) by Statistics Canada (2016) was one of the first efforts to collect data on technology adoption on Canadian farms (Duncan 2018). The list of technologies changed in the next COA in 2021 making it difficult to analyze the tends in technology adoption (Statistics Canada 2021). The adoption rates of various technologies within the Canadian crop sector exhibit significant variation, depending upon factors such as survey methodology, respondent demographics, and regional geography. For instance, the adoption of DATs among Ontario grain farmers has been reported at varying rates: 67% by the COA in 2016, 65.4% by COA in 2021, 96% by Mitchell, Weersink, and Erickson (2018), and 73% by Ruder (2019). These discrepancies do not necessarily reflect changing trends in DAT adoption among Ontario crop farmers but are largely attributed to variations in the types of technologies considered, differences in respondent demographics, and sample sizes across the studies.

The adoption rates also vary significantly for different technologies. Table 10 presents a summary of adoption rate of various agriculture technologies in Canada crop farms per Census of Agriculture 2021. Autosteer systems are utilized by 67% of oilseed and grain farms, whereas Geographic Information Systems (GIS) and Variable Rate Applications (VRT) are adopted by only 32% and 35% of farms, respectively. The variation in adoption rates for GPS technologies, such as auto-steer systems, compared to more complex PA tools like variable rate application technologies, illustrates a critical factor influencing adoption: the balance between value added and the associated costs. Auto-steer systems, which require minimal additional skills, have higher adoption rates, whereas technologies necessitating new skills and decision-making models face lower adoption due to the perceived complexity and required investment in knowledge and resources (Mitchell, Weersink, and Erickson 2018). Duncan (2023) surveyed 964 Canadian crop producers using digital technologies and found that 33% were high-tech adopters, utilizing both basic and intermediate technologies like autosteer and farm management software. In contrast, 72% were categorized as low-tech adopters.

Table 10 Technology adoption in Canadian Crop Farms

Technology adoption rates in Canadian Crop Farms* - Census 2021									
Type of Crop Farms	**Farm Sizes**	**Total number of farms**	**Farms reporting use of technologies**	**Use of automated steering (auto-steer)**	**Use of GIS mapping (e.g., soil mapping)**	**Variable rate input application**	**Drones**	**Soil sample test**
			% of total farms	% of reporting farms	% of reporting farms	% of reporting farms	% of reporting farms	% of reporting farms
Oilseed & grain farming	Small farms (>70 acres)	5476	57.3	39.1	32.3	39.2	3.6	54.1
	Mid-sized farms (<70 acres >2240 acres)	48336	77.7	67.9	31.1	34.6	6.5	60.4
	Large-sized farms (>2240 acres)	11323	96.6	96.4	43.9	42.4	14.0	68.7
	All oilseed & grain farms	65135	79.2	72.2	33.9	36.5	7.9	61.8
Other crop farming	Small farms (>70 acres)	7346	17.4	13.7	13.0	20.4	4.3	51.6
	Mid-sized farms (<70 acres >2240 acres)	22362	27.8	29.8	15.8	23.5	5.9	59.4
	Large-sized farms (>2240 acres)	802	65.1	74.5	25.3	32.0	11.5	51.0
	All other crop farms	30510	26.3	30.1	16.0	23.5	6.0	57.6
All Crop Farms		**95645**	**62.3**	**66.5**	**31.5**	**34.8**	**7.6**	**61.2**

* Data reported on principal field crops per Table: 32-10-0359-01 classification of Statistics Canada (2021)

The adoption rates also vary with how the question is farmed about a particular technology and the findings of different studies are not objectively comparable. For example, the adoption rate of Geographic Information Systems (GIS) according to the Statistics Canada (2021), is notably lower than that of variable rate application of inputs (VRA), even though VRA typically follow GIS-based soil mapping. The questionnaire in this study asks about variable rate input application in general, rather than focusing on specific technologies or equipment. In many cases, zone delineation is performed using traditional grid soil sampling and testing, with inputs applied based on soil test results. This process doesn't always require the use of rate controllers or section controls that operate with GIS for pre-planned input applications like fertilizers, herbicides, pesticides, or seeding. This may explain the higher adoption rate of VRA compared to GIS-based soil mapping. However, the percentage of respondents using soil sampling is significantly higher than both, reinforcing this observation.

DAT Adoption Dynamics:

The different approaches to study the adoption dynamics have led researchers to draw different conclusions about the level of adoption of DAT by Canadian crop framers. All studies included in this review that surveyed farmers reported adoption rates of high-tech DATs, such as field mapping, variable rate technologies, and digital imagery, to be approximately 50% or lower (Duncan 2023; Ruder 2019). The interpretation of these rates is subjective, with Mitchell, Weersink, and Erickson (2018), and Jim Timlick (2023) classifying them as indicative of low adoption, while Duncan (2023) and Lorraine A. Nicol and Nicol

(2018) views them as relatively high. There is yet another challenge interpreting the results from these studies: the use of DATs does not always reflect the use of data for farming decisions. Duncan (2023) found that five percent of the crop producers who were using DATs did not collect or store any data. The percentage of DAT users who do not utilize data for informed decision-making is likely even higher, raising concerns about whether adoption rates truly reflect comprehensive or effective integration of digital agriculture practices.

The STS literature has also on attempted to explore the relationship between farmers' demographic and farm characteristics and technology adoption. Large sized farms generally exhibit higher field variability than smaller farms and DAT adoption improves productivity by efficient management of soils, inputs, and crops. The COA 2021 results reveal that large sized (greater than 2240 acres) oil seed and grain farms are generally more likely to adopt DATs as compared to farmers of other crop or small-sized farms (less than 71 acres). Duncan (2023) also finds similar results and associates age and experience as factors affecting adoption DATs. Their study does not find education level as a significant factor, a result also drawn by L A Nicol and Nicol (2021) for Southern Albertan and Steele 2017 for Western Canadian crop farmers. While there is no conclusive evidence in Canadian literature on the role of demographics in technology adoption, several barriers have been identified. These barriers include financial pressures for farmers, the high cost of technologies, farmers perceiving the costs of PA technologies outweighing the benefits they receive, lack of technical knowledge, poor rural internet connectivity, and producers having little confidence in agronomic recommendations provided by vast amounts of data generated (Mitchell, Weersink, and Bannon 2021; L A Nicol and Nicol 2021; Steele 2017). Low adoption rates may also stem from insufficient communication regarding the benefits and potential impact of digital technologies on agricultural productivity and sustainability. Addressing these barriers requires a collaborative effort involving government support, industry initiatives, educational programs, and technological advancements tailored to the specific needs and challenges faced by Canadian farmers (Phillips et al. 2019).

Data Management and Power Dynamics:

The adoption of DATs is a business decision and depends on a variety of factors. Rose et al. (2016) discussed fifteen factors affecting the use of decision support tools, most of which have are relevant to the adoption of DATs in Canada. The growing emphasis on PA, which relies heavily on extensive data collection and processing through DATs has introduced new challenges related to data usage, ownership, and security. The qualitative research in Canadian context that explores the socio-technical dimensions of DATs and the extensive amount of data generated can be grouped into the following three broad categories.

Data Ownership, Control and Governance:

Since data is central to PA and digital agriculture, questions about data ownership and its interoperability across platforms and equipment from different vendors have been widely discussed in the literature (see Bronson and Knezevic 2016; Murray Fulton et al. 2021; Soma and Nuckchady 2021; Mitchell, Weersink, and Erickson 2018). The debate on these issue ranges from farmers' lack of clarity on terms and conditions of using DATs which in many cases limits their ability to use it on a different equipment or platforms. Large vertically integrated companies like John Deere (JD) offer data analytics platforms to process data collected by their equipment and share insights with farmers. However, access to the raw data is restricted by contractual terms that allow the equipment manufacturers to maintain control over the data (Rotz, Duncan, et al. 2019). Farmers have limited influence over giving consent for the use of their data and the sharing of farm data with third parties, making this a challenging issue in ethical marketing of DATs (Soma and Nuckchady 2021).

Digital Power Concentration*:*

One consequence of data ownership and control by equipment manufacturers is the concentration of market power among large corporations. Despite generating the data, farmers often lack access even to aggregated and anonymized versions of their own farm data, as international agreements tend to prioritize software protection over farmers' rights to data (Bronson 2019). This has led to the development of new market structures, shaped by the formality of contractual arrangements and varying levels of interoperability.

(Phillips et al. 2019) categorize DAT and service providers in Western Canada into four distinct market structures, with the corporate model—exemplified by companies like John Deere—being characterized by closed systems and limited interoperability. This lack of flexibility, combined with the manufacturers' retention of the 'right to repair,' creates a lock-in effect, forcing farmers into long-term reliance on specific DATs and providers (Soma and Nuckchady 2021). Such concentrated market power increases farmers' dependency on these corporations, allowing them to influence market trends, research priorities, and even public policy to their advantage, further entrenching the power imbalance in the agricultural sector.

Privacy, Security, and Ethical Implications:

The integration of DATs has diverse impacts on social dynamics and human values, from individual data privacy concerns to broader data sovereignty challenges. When equipment manufacturers control farm data, farmers lose autonomy over how their data—whether anonymized or not—is used, shared, and monetized. This lack of control also raises concerns about data security, with farmers fearing equipment hacking and breaches of personal data (Fulton et al., 2021). Many companies, such as John Deere and Bayer, are headquartered outside Canada, meaning that the data they store, and process is subject to foreign laws. This presents significant challenges to data sovereignty and security, as control over digital knowledge in agriculture may become a modern form of land acquisition in the 21st century, given the growing value of big data (Duncan 2023; Murray Fulton et al. 2021; Soma and Nuckchady 2021).

Data sovereignty is also particularly relevant for Indigenous communities whose cultural practices are tied to land and agriculture. The use of their agricultural data without proper consent risks the exploitation of their privacy and traditional knowledge. Furthermore, as Bronson (2019) note, DATs are predominantly designed for large farms and major crops, which deepens the divide between farmers who can afford these capital-intensive technologies and those who cannot. This raises broader questions about equity and access in the adoption of DATs, particularly for smallholders and marginalized communities.

DISCUSSION:

This scoping review takes a holistic view of the innovation process, examining it from the ideation and research & development (R&D) phases through to commercialization, adoption, and diffusion within Canadian crop production systems. By integrating both technical and qualitative data within this sectoral innovation framework, we aim to develop a nuanced understanding of DAT innovations and the dynamics shaping their adoption. We present findings from research on the development, validation, and adoption of DATs. The results discussed stem from experimental studies on various DATs, focusing on the validation of data processing methods. These studies predominantly explore the use of proximal and remote sensing techniques for estimating or predicting soil and crop properties, yield forecasting, fertilizer optimization, and weed control. Proximal soil sensing (PSS) offers non-invasive, real-time measurement of soil properties, with sensor selection tailored to specific attributes for better accuracy. On-the-go sensors, though efficient, may disrupt soil, prompting the development of tools like the OSA, which minimizes disturbance in harder-to-access areas. Remote sensing with satellites and UAVs provides scalable insights into soil and crop properties; high-resolution sensors like RapidEye and Sentinel-2 allow for detailed zone delineation, aiding precision management practices such as variable-rate nitrogen application. Thematic maps created through digital soil mapping (DSM), supported by machine learning, integrate multiple data sources to improve soil property predictions, supporting more informed and sustainable management. Soil moisture estimation also benefits from active and passive satellite sensors like SAR and L-band radiometers, although vegetation interference remains a limitation. Ongoing model improvements, such as the Water Cloud Model, aim to enhance moisture predictions. Machine learning supports soil moisture estimation and emerging methods like cell phone imaging of soil organic matter, although data accuracy is affected by vegetation cover.

Precision agriculture faces significant challenges in capturing high spatial variability across fields (Hosseini et al. 2015). Remote sensing addresses this issue through multispectral and hyperspectral Earth observation images that analyze the spectral signatures of vegetation and soil. These spectral signatures support early-stage crop monitoring, though environmental factors like cloud cover can sometimes hinder their accuracy. Synthetic Aperture Radar (SAR) sensors offer a solution by operating independently of weather conditions, making them particularly valuable in regions with frequent cloud cover (Ghosh et al. 2022).

Advances in machine learning and deep neural networks have significantly enhanced the estimation of crop biophysical parameters, such as biomass, canopy nitrogen weight, and chlorophyll content. Deep learning approaches, particularly deep artificial neural networks, exhibit strong predictive capabilities, especially when paired with SAR polarimetric data and vegetation indices (Bahrami et al. 2021). Moreover, models like the Water Cloud Model (WCM) effectively estimate microwave backscattering coefficients over vegetation-covered surfaces, supporting precise assessments of soil and crop moisture (Ghosh et al. 2022). For crop yield prediction, remote sensing tools rely on vegetation indices (e.g., NDVI, EVI) and agroecosystem models (e.g., DSSAT) to analyze crop responses under diverse conditions. These diverse DATs contribute to data-driven agriculture, offering valuable insights for producers and policymakers, though variability in crop types, methods, and conditions requires ongoing validation.

This review focused on studies conducted from 2013 onward to capture recent developments and newer validation studies. Many studies utilized mature digital technologies available commercially, though these tools often served as validation frameworks for testing new data analysis methods. Notably, the accuracy of DAT applications depends heavily on specific variables such as soil and crop types, data sources, machine learning techniques, and regional agroclimatic conditions. High-resolution, high-frequency data from satellite or drone imagery, combined with multiple sensors, tend to improve predictions for soil properties, crop yields, and disease detection. However, no single algorithm can consistently predict or map soil and crop properties across all conditions, underscoring the need for algorithms tailored to specific data types, crop-soil combinations, and regional applications.

Decision support systems (DSSs), such as DSSAT models, show promising results in simulating crop growth and yield by integrating soil, climate, and farm management data. However, like other DATs, these models are often validated under limited conditions, and their insights depend on high-quality data. Equipment manufacturers and service providers are the primary users of these tools, while farmers, as secondary users, rely on the predictions for decisions on planting, fertilization, and irrigation. Achieving robust outcomes from these tools requires that machine learning and other models be trained with datasets from diverse regions, such as various provinces in Canada. The studies included in this review reveal that the research is disproportionately concentrated in Eastern Canada. Among the 35 experimental studies fully or partially funded by federal government agencies, the majority were conducted in Ontario (seventeen) and Quebec (six), while only seven studies took place in Western Canada, a region critical to the production of principal field crops. This uneven distribution underscores a geographic imbalance in research efforts within Canada's agricultural sector. Additionally, a disparity exists in research funding sources: more than half of the studies were supported fully or partially by federal agencies, whereas only a quarter received provincial funding. Improving the spatial distribution of research efforts will require enhanced coordination between federal and provincial funding bodies. A similar pattern was observed in research on emission estimation methodologies for Canada, further indicating the need for better alignment within the country's research funding ecosystem. Given Canada's diverse cropping systems and climatic conditions, there is a critical need to refine and validate these models under a wider range of scenarios before widespread adoption by farmers or technology service providers can be recommended.

Overall, this review presents forward-looking research on DATs, many of which are still in the prototype phase and far from commercialization. Advanced sensor systems, such as soil analyzers and multi-sensor platforms, require further validation and model refinement before moving into production. Adoption of these DATs will come much later in the innovation process. However, much of the literature emphasizes the importance of exploring not only the technical development of DATs but also the socio-cultural dimensions and challenges that may arise with their widespread adoption, particularly related to the collection and processing of large amounts of farm data. A major concern in this context is data ownership and control. Farmers often find themselves on the losing side, as large corporations own and control the data. However, the data is often aggregated, and individual farm data has limited standalone value. One proposed way to address this imbalance is by compensating farmers through dividends derived from corporate profits, as the data contributes to product development and improved services.

Several initiatives aim to address issues of data interoperability and transparency. For instance, the 'Ag Data Transparent' initiative certifies companies that follow key principles, including simple contracts, farmer ownership of data, transparency in data use, and data portability. Portability ensures that farmers can transfer their data to other platforms unless it has been aggregated. Additionally, international standards such as ISOBUS (ISO 11783) and ADAPT's open-source plug-and-play model enhance the integration of PA tools, promoting more transparent and efficient data use (Phillips et al. 2019). Big AgTech companies like John Deere have started joining these initiatives, transitioning from closed, top-down market models to more networked models that involve transactional data exchanges between farmers and purchasers.

The research on technical and sociopolitical aspects of DATs in Canada reveals a layered and evolving innovation landscape. While experimentation and validation of DATs are significantly advancing, their transition DATs into production and adoption phases hinge upon the strength of innovation of ecosystem with diverse actors. However, the discourse on DATs revolves around manufacturers and places little emphasis on farmers and their needs and challenges. Some authors discuss the implications of the inherently skewed approach and suggests inclusion of all stakeholders and their perspectives in the innovation process to achieve the intended outcomes of digital transition.

CONCLUSION AND POLICY RECOMMENDATIONS:

The review of Digital Agricultural Technologies (DATs) in Canada reveals the complexity of integrating innovative digital tools into crop production, shaped by both technical advancements and socio-political factors. Canada's distinct innovation framework, characterized by public sector-led research funding, influences how DATs are developed, validated, and adopted. While the technical studies provide valuable insights into the potential of emerging technologies like proximal and remote sensing systems, the socio-technical dimension cannot be overlooked.

The adoption and diffusion of DATs are not merely technical matters but are influenced by institutional, regulatory, and social factors unique to Canada, including emission reduction targets, market competitiveness as a food exporter, and data sovereignty issues. Furthermore, as many technologies are still in experimental stages, their widespread use has yet to be fully realized, underscoring the need for continued research and validation across diverse Canadian agro-climatic conditions.

By focusing on the Canadian context, this review provides a nuanced understanding of the barriers, drivers, and frameworks shaping DAT adoption, laying the groundwork for future policy directions that promote responsible research and innovation while addressing data governance, privacy, and security concerns. The synthesis of both technical and social science literature emphasizes that, while Canada has the potential to lead in digital agriculture, it must navigate these challenges to ensure the successful, sustainable integration of DATs into its agricultural systems.

This study has several limitations. The research highlight results of the DATs and methods that are in the development and validation stage and does not capture the full spectrum of technologies under commercial use or their successes and adoption challenges. Findings of this study are specific to Canadian crop production sector and may not be entirely generalizable to other jurisdictions. This also excludes comparative insights from other countries and misses out on lessons learned from international best practices that could be applicable to Canadian research. Future research could focus on these areas and review the role of policy frameworks in shaping the future of DAT diffusion by strengthening the innovation ecosystem.

Based on findings from the reviewed studies and insights generated through this scoping review, several policy recommendations emerge to facilitate the development and broader adoption of DATs in Canada:

Enhance Collaboration Across the Innovation Ecosystem: Policymakers should promote greater collaboration among key stakeholders, including farmers, equipment manufacturers, venture capitalists, and researchers, ensuring that all parties are involved early in the design, validation, and scaling stages. By aligning innovations with the practical needs of farmers and securing venture capital support, the commercialization of DATs can be accelerated. The normative STS studies propose an RRI framework with a systematic inclusion of stakeholder - farmers, researchers, funders, technology developers and policymakers - to enhance the social and ethical appropriateness of DATs (Bronson 2018; Duncan 2023; Ebrahimi, Sandra Schillo, and Bronson 2021). RRI can potentially address issues regarding equity in research funding, gains distribution of dividends from technological advancement, addressing market monopolies, fairness in data ownership and sustaining social and ecological.

Optimize Research Funding Allocation: To enhance the effectiveness and future applicability of DATs in Canada, it is recommended that federal research funding be strategically diversified to support spatially varied studies across the country, particularly in crop-dense western provinces. Given that federal funding is a major source, a target-oriented allocation of resources should be implemented to focus on regions with high agricultural output, such as Saskatchewan, Alberta, and Manitoba. This would ensure that more field data is gathered from areas where it is most relevant for DAT development and deployment. By expanding the geographic distribution of funded research, policymakers can promote the generation of region-specific data that better reflects Canada's diverse agroecological conditions, ultimately leading to more robust and scalable DAT solutions for Canadian agriculture.

Strengthen Coordination in Research Funding: Improved coordination between federal and provincial funding agencies is essential to promote more comprehensive data collection from diverse agroclimatic regions and cropping systems across Canada. This will enhance the accuracy of DAT applications, ensuring that technologies reflect the distinct conditions of Canadian agriculture.

Promote Data Interoperability and Transparency: While regulatory interventions are often met with skepticism, policies that incentivize initiatives such as ‘Ag Data Transparent’ can foster greater transparency and trust in data ownership, use, and privacy. Encouraging data interoperability ensures that farmers can access and utilize their data across platforms, promoting broader adoption.

Encourage Private Sector Involvement in Research and Commercialization: Canada’s research funding framework is predominantly public sector-driven, particularly by federal agencies. This lack of private-sector engagement has hindered commercialization support for startups emerging from universities. To address this, policymakers should incentivize private-sector involvement through measures like R&D tax credits, fostering public-private partnerships, creating innovation hubs, and expanding co-funded programs to bridge the gap between research and market adoption.

Adopt an RRI Framework: Policymakers should integrate ethical and equity considerations into the DAT innovation process using the RRI framework. This approach ensures that issues such as social inclusion, data governance, and transparency are addressed early in the development and deployment of DATs, ultimately guiding policy recommendations that promote inclusive and socially responsible innovation in the agri-tech sector.

These recommendations aim to foster a more robust and inclusive innovation ecosystem, ensuring that DATs are not only technologically advanced but also widely adopted, equitable, and socially responsible.

REFERENCES:

AAFC. 2024. “Canada: Outlook for Principal Field Crops, 2024-10-21 - Agriculture.Canada.Ca.” 2024. https://agriculture.canada.ca/en/sector/crops/reports-statistics/canada-outlook-principal-field-crops-2024-10-21.

Abbasi, Rabiya, Pablo Martinez, and Rafiq Ahmad. 2022. “The Digitization of Agricultural Industry – a Systematic Literature Review on Agriculture 4.0.” Smart Agricultural Technology. Elsevier B.V. https://doi.org/10.1016/j.atech.2022.100042.

Abbes, Ali Ben, Ramata Magagi, and Kalifa Goita. 2019. “Soil Moisture Estimation From Smap Observations Using Long Short- Term Memory (LSTM).” In , 1590–93. https://doi.org/10.1109/IGARSS.2019.8898418.

Abiri, Rambod, Nastaran Rizan, Siva K. Balasundram, Arash Bayat Shahbazi, and Hazandy Abdul-Hamid. 2023. “Application of Digital Technologies for Ensuring Agricultural Productivity.” Heliyon 9 (12): e22601. https://doi.org/10.1016/J.HELIYON.2023.E22601.

Adamchuk, Viacheslav I, and Nandkishor Dhawale. 2014. “Development of On-the-Spot Soil Analyzer for Measuring Soil Chemical Properties.” In 12th International Conference on Precision Agriculture, Sacramento, California, USA. https://www.researchgate.net/publication/273966174_Development_of_on-the-spot_soil_analyzer_for_measuring_soil_chemical_properties.

Agyemang, Prince, and Ebenezer Miezah Kwofie. 2021. “Response-to-Failure Analysis of Global Food System Initiatives: A Resilience Perspective.” Frontiers in Sustainable Food Systems. Frontiers Media S.A. https://doi.org/10.3389/fsufs.2021.676997.

Akhavan, Z, M Hasanlou, M Hosseini, and H McNairn. 2021. “Decomposition-Based Soil Moisture Estimation Using UAVSAR Fully Polarimetric Images.” Agronomy 11 (1). https://doi.org/10.3390/agronomy11010145.

Ali, Iftikhar, Felix Greifeneder, Jelena Stamenkovic, Maxim Neumann, and Claudia Notarnicola. 2015. “Review of Machine Learning Approaches for Biomass and Soil Moisture Retrievals from Remote Sensing Data.” Remote Sensing 2015, Vol. 7, Pages 16398-16421 7 (12): 16398–421. https://doi.org/10.3390/RS71215841.

Altdorff, D, K Sadatcharam, A Unc, M Krishnapillai, and L Galagedara. 2020. “Comparison of Multi-Frequency and Multi-Coil Electromagnetic Induction (EMI) for Mapping Properties in Shallow Podsolic Soils.” Sensors 20 (8). https://doi.org/10.3390/s20082330.

Badewa, E, A Unc, M Cheema, and L Galagedara. 2019. “Temporal Stability of Soil Apparent Electrical Conductivity (ECa) in Managed Podzols.” ACTA GEOPHYSICA 67 (4): 1107–18. https://doi.org/10.1007/s11600-019-00306-1.

Bahrami, H, S Homayouni, A Safari, S Mirzaei, M Mahdianpari, and O Reisi-Gahrouei. 2021. "Deep Learning-Based Estimation of Crop Biophysical Parameters Using Multi-Source and Multi-Temporal Remote Sensing Observations." Agronomy 11 (7). https://doi.org/10.3390/agronomy11071363.

Bergek, Anna, Staffan Jacobsson, Bo Carlsson, Sven Lindmark, and Annika Rickne. 2008. "Analyzing the Functional Dynamics of Technological Innovation Systems: A Scheme of Analysis." Research Policy 37 (3): 407–29. https://doi.org/10.1016/J.RESPOL.2007.12.003.

Bi, L N, O Wally, G P Hu, A U Tenuta, Y R Kandel, and D S Mueller. 2023. "A Transformer-Based Approach for Early Prediction of Soybean Yield Using Time-Series Images." FRONTIERS IN PLANT SCIENCE 14. https://doi.org/10.3389/fpls.2023.1173036.

Bourassa, Joshua, and Elena Vinco. 2022. "Global Agricultural Greenhouse Gas Emissions: Enteric Methane." Calgary.

Bouroubi, Yacine, Nicolas Tremblay, Philippe Vigneault, and Mathieu Benoit. 2014. "Linear Spectral Unmixing for Crop and Soil Information Extraction from a Single Worldview-2 Image." In 2014 IEEE Geoscience and Remote Sensing Symposium, 5103–6. https://doi.org/10.1109/IGARSS.2014.6947645.

Bronson, Kelly. 2018. "Smart Farming: Including Rights Holders for Responsible Agricultural Innovation." TIM Review 8 (2): 7–14. https://doi.org/10.22215/timreview/1135.

———. 2019. "Looking through a Responsible Innovation Lens at Uneven Engagements with Digital Farming." NJAS - Wageningen Journal of Life Sciences 90–91 (December). https://doi.org/10.1016/j.njas.2019.03.001.

Bronson, Kelly, and Irena Knezevic. 2016. "Big Data in Food and Agriculture." Http://Dx.Doi.Org/10.1177/2053951716648174 3 (1). https://doi.org/10.1177/2053951716648174.

———. 2019. "The Digital Divide and How It Matters for Canadian Food System Equity." Canadian Journal of Communication 44 (2): 63–68. https://doi.org/10.22230/cjc.2019v44n2a3489.

Burdett, H, and C Wellen. 2022. "Statistical and Machine Learning Methods for Crop Yield Prediction in the Context of Precision Agriculture." Precision Agriculture 23 (5): 1553–74. https://doi.org/10.1007/s11119-022-09897-0.

Busse, M., A. Doernberg, R. Siebert, A. Kuntosch, W. Schwerdtner, B. König, and W. Bokelmann. 2014a. "Innovation Mechanisms in German Precision Farming." Precision Agriculture 15 (4): 403–26. https://doi.org/10.1007/S11119-013-9337-2/FIGURES/4.

———. 2014b. "Innovation Mechanisms in German Precision Farming." Precision Agriculture 15 (4): 403–26. https://doi.org/10.1007/S11119-013-9337-2/FIGURES/4.

Calvet, Jean Christophe, Jean Pierre Wigneron, Jeffrey Walker, Fatima Karbou, André Chanzy, and Clément Albergel. 2011. "Sensitivity of Passive Microwave Observations to Soil Moisture and Vegetation Water Content: L-Band to W-Band." IEEE Transactions on Geoscience and Remote Sensing 49 (4): 1190–99. https://doi.org/10.1109/TGRS.2010.2050488.

Canadian Chamber of Commerce. 2024. "Policy Matters: Advancing Canada's Agriculture and Agri-Food Sector." Canadian Chamber of Commerce. https://chamber.ca/policy-matters-advancing-canadas-agriculture-and-agri-food-sector/.

Capmourteres, Virginia, Justin Adams, Aaron Berg, Evan Fraser, Clarence Swanton, and Madhur Anand. 2018. "Precision Conservation Meets Precision Agriculture: A Case Study from Southern Ontario." Agricultural Systems 167 (November):176–85. https://doi.org/10.1016/j.agsy.2018.09.011.

Champagne, C, T Rowlandson, A Berg, T Burns, J L'Heureux, E Tetlock, J R Adams, H McNairn, B Toth, and D Itenfisu. 2016. "Satellite Surface Soil Moisture from SMOS and Aquarius: Assessment for Applications in Agricultural Landscapes." International Journal of Applied Earth Observation and Geoinformation 45 (Part B): 143–54. https://ezproxy.lib.ucalgary.ca/login?url=https://search.ebscohost.com/login.aspx?direct=true&db=lah&AN=20163028729&site=ehost-live.

Das, Mohana. 2021. "Deepveg: Deep Learning for Multiclass Segmentation of Weed, Canola and Canola Damage." Canada – Saskatchewan, CA: The University of Regina (Canada). https://www.proquest.com/pqdtglobal/docview/2652596135/abstract/EFC0E39AD96B4F92PQ/26.

Dhawale, N M, V I Adamchuk, S O Prasher, R A V Rossel, and A A Ismail. 2022. "Evaluation of Two Portable Hyperspectral-Sensor-Based Instruments to Predict Key Soil Properties in Canadian Soils." Sensors 22 (7). https://doi.org/10.3390/s22072556.

Dhawale, Nandkishor Motiram. 2015. "Advances in Proximal Soil Sensing through Integrated Systems Approach." Canada – Quebec, CA: McGill University (Canada). https://www.proquest.com/pqdtglobal/docview/2519369041/abstract/EFC0E39AD96B4F92PQ/86.

Dhillon, G S, L Baarda, M Gretzinger, and K Coles. 2022. "Effect of Precision Planting and Seeding Rates on Canola Plant Density and Seed Yield in Southern Alberta." Canadian Journal of Plant Science 102 (3): 698–709. https://doi.org/10.1139/cjps-2020-0186.

Dohoo, I R, W S Martin, and H Stryhn. 2009. Veterniary Epidemiologic Research. Edited by M McPike. Veterinary Epidemiologic Research. 2nd ed. Canada: VER, Incorporated, 2009. https://books.google.com/books/about/Veterinary_Epidemiologic_Research.html?id=sniqQwAACAAJ.

Dong, Taifeng, Jiali Shang, Jiangui Liu, Budong Qian, Qi Jing, Baoluo Ma, Ted Huffman, et al. 2019. "Using RapidEye Imagery to Identify Within-Field Variability of Crop Growth and Yield in Ontario, Canada." Precision Agriculture 20 (6): 1231–50. https://doi.org/10.1007/s11119-019-09646-w.

Duncan, Emily. 2018. "An Exploration of How the Relationship between Farmers and Retailers Influences Precision Agriculture Adoption." Guleph, Ontario. https://www.google.com/url?sa=t&source=web&rct=j&opi=89978449&url=https://atrium.lib.uoguelph.ca/items/48af86e3-e828-40e9-80c5-d0e8840e5aa9&ved=2ahUKEwiFyYST9raJAxUuFTQIHRGDFj0QFnoECBsQAQ&usg=AOvVaw3YGJnbIW51d9Te3NmcPp1u.

———. 2023. "The Affordances of Digital Agricultural Technologies." Guelph, Ontario. https://atrium.lib.uoguelph.ca/items/f2cd5143-e20d-445c-a2f9-8d7c942a3877.

Duncan, Emily, Alesandros Glaros, Dennis Z Ross, and Eric Nost. 2021. “New but for Whom? Discourses of Innovation in Precision Agriculture.” Agric Hum Values 38 (4): 1181–99. https://doi.org/10.1007/s10460-021-10244-8.

Ebrahimi, Hassan P., R. Sandra Schillo, and Kelly Bronson. 2021. “Systematic Stakeholder Inclusion in Digital Agriculture: A Framework and Application to Canada.” Sustainability (Switzerland) 13 (12). https://doi.org/10.3390/su13126879.

ECCC. 2020. “A Healthy Environment and a Healthy Economy.” Gatineau QC. https://www.canada.ca/content/dam/eccc/documents/pdf/climate-change/climate-plan/healthy_environment_healthy_economy_plan.pdf.

———. 2023. “National Inventory Report 2023 - Part 1.” https://publications.gc.ca/site/archivee-archived.html?url=https://publications.gc.ca/collections/collection_2023/eccc/En81-4-2021-1-eng.pdf.

Eyre, R, J Lindsay, A Laamrani, and A Berg. 2021. “Within-Field Yield Prediction in Cereal Crops Using LiDAR-Derived Topographic Attributes with Geographically Weighted Regression Models.” REMOTE SENSING 13 (20). https://doi.org/10.3390/rs13204152.

Françis, Frédéric, and René - Laforest. 2015. “Real-Time Variable Control Technologies for Precision Agriculture.”

Ghosh, S S, S Dey, N Bhogapurapu, S Homayouni, A Bhattacharya, and H McNairn. 2022. “Gaussian Process Regression Model for Crop Biophysical Parameter Retrieval from Multi-Polarized C-Band SAR Data.” REMOTE SENSING 14 (4). https://doi.org/10.3390/rs14040934.

Glenn, Aaron J, Alan P Moulin, Amal K Roy, and Henry F Wilson. 2021. “Soil Nitrous Oxide Emissions from No-till Canola Production under Variable Rate Nitrogen Fertilizer Management.” Geoderma 385 (March):114857. https://doi.org/10.1016/j.geoderma.2020.114857.

GoC. 2023. Canadian Net-Zero Emissions Act. Canada: http://laws-lois.justice.gc.ca.

Gogoi, Jumi, Nathaniel K. Newlands, Zia Mehrabi, Nicholas C. Coops, and Navin Ramankutty. 2023. “Assessing the Performance of Satellite-Based Models for Crop Yield Estimation in the Canadian Prairies.” Canadian Journal of Remote Sensing 49 (1). https://doi.org/10.1080/07038992.2023.2252926.

Green, Heidi, Ritin Fernandez, and Catherine MacPhail. 2021. “The Social Determinants of Health and Health Outcomes among Adults during the COVID-19 Pandemic: A Systematic Review.” Public Health Nursing 38 (6): 942–52. https://doi.org/10.1111/PHN.12959.

Hailu, Getu. 2023. “Reflections on Technological Progress in the Agri-Food Industry: Past, Present, and Future.” Canadian Journal of Agricultural Economics 71 (1): 119–41. https://doi.org/10.1111/cjag.12325.

Hengl, Tomislav, Markus G. Walsh, Jonathan Sanderman, Ichsani Wheeler, Sandy P. Harrison, and Iain C. Prentice. 2018. “Global Mapping of Potential Natural Vegetation: An Assessment of Machine Learning Algorithms for Estimating Land Potential.” PeerJ 2018 (8): e5457. https://doi.org/10.7717/PEERJ.5457/FIG-16.

Higgins, Vaughan, Melanie Bryant, Andrea Howell, and Jane Battersby. 2017. "Ordering Adoption: Materiality, Knowledge and Farmer Engagement with Precision Agriculture Technologies." Journal of Rural Studies 55 (October):193–202. https://doi.org/10.1016/J.JRURSTUD.2017.08.011.

Hosseini, Mehdi, Heather McNairn, Amine Merzouki, and Anna Pacheco. 2015. "Estimation of Leaf Area Index (LAI) in Corn and Soybeans Using Multi-Polarization C- and L-Band Radar Data." Remote Sensing of Environment 170 (December):77–89. https://doi.org/10.1016/j.rse.2015.09.002.

Huang, Hsin-Hui. 2007. "Leveraging Geospatial Data to Improve Soil Characterization for Precision Agriculture." Ste. Anne de Bellevue, Québec. https://www.proquest.com/pqdtglobal/docview/2507712702/fulltextPDF/F6566318EC3C4D4EPQ/1?accountid=9838&sourcetype=Dissertations%20&%20Theses.

———. 2017. "Leveraging Geospatial Data to Improve Soil Characterization for Precision Agriculture."

Ishaque, Hanan, Joshua Bourassa, and Guillaume Lhermie. 2024. "Navigating Climate Change: Alberta's Carbon Program for Sustainable Agriculture." The School of Public Policy Publications 17 (1). https://doi.org/10.55016/ojs/sppp.v17i1.79439.

ISPA. 2024. "Precision Ag Definition | International Society of Precision Agriculture." 2024. https://www.ispag.org/about/definition.

Ji WenJun, V I Adamchuk, Chen SongChao, A S M Su, A Ismail, Gan QianJun, Shi Zhou, and Asim Biswas. 2019. "Simultaneous Measurement of Multiple Soil Properties through Proximal Sensor Data Fusion: A Case Study." Geoderma 341:111–28. https://doi.org/10.1016/j.geoderma.2019.01.006.

Jim Timlick. 2023. "Precision Ag Panel Spells out Benefits and Slow Adoption Rate." Grainews. Precision.

Jing, Qi, Jiali Shang, Budong Qian, Gerrit Hoogenboom, Ted Huffman, Jiangui Liu, Bao Luo Ma, et al. 2016. "Evaluation of the CSM-CROPGRO-Canola Model for Simulating Canola Growth and Yield at West Nipissing in Eastern Canada." Agronomy Journal 108 (2): 575–84. https://doi.org/10.2134/agronj2015.0401.

Killeen, Patrick, Iluju Kiringa, Tet Yeap, and Paula Branco. 2024. "Corn Grain Yield Prediction Using UAV-Based High Spatiotemporal Resolution Imagery, Machine Learning, and Spatial Cross-Validation." Remote Sensing 16 (4). https://doi.org/10.3390/rs16040683.

Klerkx, Laurens, Emma Jakku, and Pierre Labarthe. 2019. "A Review of Social Science on Digital Agriculture, Smart Farming and Agriculture 4.0: New Contributions and a Future Research Agenda." NJAS - Wageningen Journal of Life Sciences. Elsevier B.V. https://doi.org/10.1016/j.njas.2019.100315.

Klerkx, Laurens, and Cees Leeuwis. 2009. "Establishment and Embedding of Innovation Brokers at Different Innovation System Levels: Insights from the Dutch Agricultural Sector." Technological Forecasting and Social Change 76 (6): 849–60. https://doi.org/10.1016/J.TECHFORE.2008.10.001.

Laamrani, A, A A Berg, P Voroney, H Feilhauer, L Blackburn, M March, P D Dao, Y He, and R C Martin. 2019. "Ensemble Identification of Spectral Bands Related to Soil Organic Carbon Levels over an Agricultural Field in Southern Ontario, Canada." Remote Sensing 11 (11). https://doi.org/10.3390/rs11111298.

Lee, Hwang, Jinfei Wang, and Brigitte Leblon. 2020. “Using Linear Regression, Random Forests, and Support Vector Machine with Unmanned Aerial Vehicle Multispectral Images to Predict Canopy Nitrogen Weight in Corn.” Remote Sensing (Basel, Switzerland) 12 (13): 2071. https://doi.org/10.3390/rs12132071.

Lee, S J, C Choi, J Kim, M Choi, J Cho, and Y Lee. 2023. “Estimation of High-Resolution Soil Moisture in Canadian Croplands Using Deep Neural Network with Sentinel-1 and Sentinel-2 Images.” REMOTE SENSING 15 (16). https://doi.org/10.3390/rs15164063.

Lemay, M A, Allison Clark, Jeff Boggs, and Charles Conteh. 2022. “Systemic Barriers and Drivers to Technology Adoption in Canada: Lessons for Agri-Innovation in Ontario from Stakeholders of Canada’s Global Innovation Clusters.” 55. NCO Polic Brief. https://ised-isde.canada.ca/site/global-innovation-clusters/en/about-canadas-innovation-clusters-initiative.

Li JunHua, and Wang ShuSen. 2018. “Using SAR-Derived Vegetation Descriptors in a Water Cloud Model to Improve Soil Moisture Retrieval.” Remote Sensing 10 (9): 1370. https://doi.org/10.3390/rs10091370.

Li, Zhuo Ting, J. Y. Yang, W. N. Smith, C. F. Drury, R. L. Lemke, B. Grant, W. T. He, and Xiao Gang Li. 2015. “Simulation of Long-Term Spring Wheat Yields, Soil Organic C, N and Water Dynamics Using DSSAT-CSM in a Semi-Arid Region of the Canadian Prairies.” Nutrient Cycling in Agroecosystems 101 (3): 401–19. https://doi.org/10.1007/s10705-015-9688-3.

Liao, Chunhua, Jinfei Wang, Bo Shan, Yang Song, Yongjun He, and Taifeng Dong. 2023a. “Near Real-Time Yield Forecasting of Winter Wheat Using Sentinel-2 Imagery at the Early Stages.” Precision Agriculture 24 (3): 807–29. https://doi.org/10.1007/S11119-022-09975-3/TABLES/10.

———. 2023b. “Near Real-Time Yield Forecasting of Winter Wheat Using Sentinel-2 Imagery at the Early Stages.” Precision Agriculture 24 (3): 807–29. https://doi.org/10.1007/s11119-022-09975-3.

Liu, Shuang, Jingyi Yang, Xueming Yang, Craig F Drury, Rong Jiang, and W Daniel Reynolds. 2021. “Simulating Maize Yield at County Scale in Southern Ontario Using the Decision Support System for Agrotechnology Transfer Model.” Canadian Journal of Soil Science 101 (4): 734–48. https://doi.org/10.1139/cjss-2020-0116.

Lowenberg-Deboer, James, and Bruce Erickson. 2019. “Setting the Record Straight on Precision Agriculture Adoption.” Agronomy Journal 111 (4): 1552–69. https://doi.org/10.2134/AGRONJ2018.12.0779.

Ma, Bao Luo, Tian Yun Wu, and Jiali Shang. 2014. “On-Farm Comparison of Variable Rates of Nitrogen with Uniform Application to Maize on Canopy Reflectance, Soil Nitrate, and Grain Yield.” Journal of Plant Nutrition and Soil Science 177 (2): 216–26. https://doi.org/10.1002/JPLN.201200338.

Malerba, Franco. 2002. “Sectoral Systems of Innovation and Production.” Research Policy 31:247–64.

McGrath, Karen, Claire Brown, Áine Regan, and Tomás Russell. 2023. “Investigating Narratives and Trends in Digital Agriculture: A Scoping Study of Social and Behavioural Science Studies.” Agricultural Systems 207 (April):103616. https://doi.org/10.1016/J.AGSY.2023.103616.

Mitchell, Sean, Alfons Weersink, and Nicholas Bannon. 2021. “Adoption Barriers for Precision Agriculture Technologies in Canadian Crop Production.” Canadian Journal of Plant Science 101 (3): 412–16. https://doi.org/10.1139/cjps-2020-0234.

Mitchell, Sean, Alfons Weersink, and Bruce Erickson. 2018. “Adoption of Precision Agriculture Technologies in Ontario Crop Production.” Canadian Journal of Plant Science 98 (6): 1384–88. https://doi.org/10.1139/cjps-2017-0342.

Moher, David, Larissa Shamseer, Mike Clarke, Davina Ghersi, Alessandro Liberati, Mark Petticrew, Paul Shekelle, et al. 2015. “Preferred Reporting Items for Systematic Review and Meta-Analysis Protocols (PRISMA-P) 2015 Statement.” Systematic Reviews 4 (1): 148–60. https://doi.org/10.1186/2046-4053-4-1.

Murray Fulton, Marc-Andre Pigeon, Bill Oemichen, and Yang Yang. 2021. “Digital Technologies and the Big Data Revolution in the Canadian Agricultural Sector: Opportunities, Challenges, and Alternatives.” Regina. http://www.usaskstudies.coop.

Nicol, L A, and C J Nicol. 2021. “Adoption of Precision Agriculture in Alberta Irrigation Districts with Implications for Sustainability.” The Journal of Rural and Community Development 16 (1): 152–74. www.jrcd.ca.

Nicol, Lorraine A., and Christopher J. Nicol. 2018. “Adoption of Precision Agriculture to Reduce Inputs, Enhance Sustainabiltiy and Increase Food Production: A Study of Southern Alberta, Canada.” WIT Transactions on Ecology and the Environment 217:327–36. https://doi.org/10.2495/SDP180301.

O’Connor, Annette M., Brent W. Auvermann, Rungano S. Dzikamunhenga, Julie M. Glanville, Julian P.T. Higgins, Shelley P. Kirychuk, Jan M. Sargeant, Sarah C. Totton, Hannah Wood, and Susanna G. Von Essen. 2017. “Updated Systematic Review: Associations between Proximity to Animal Feeding Operations and Health of Individuals in Nearby Communities.” Systematic Reviews 6 (1). https://doi.org/10.1186/S13643-017-0465-Z.

Page, Matthew J., Joanne E. McKenzie, Patrick M. Bossuyt, Isabelle Boutron, Tammy C. Hoffmann, Cynthia D. Mulrow, Larissa Shamseer, et al. 2021. “The PRISMA 2020 Statement: An Updated Guideline for Reporting Systematic Reviews.” BMJ 372 (March). https://doi.org/10.1136/BMJ.N71.

Paul, S S, B Heung, and D H Lynch. 2022. “Modeling of Total and Active Organic Carbon Dynamics in Agricultural Soil Using Digital Soil Mapping: A Case Study from Central Nova Scotia.” CANADIAN JOURNAL OF SOIL SCIENCE. https://doi.org/10.1139/CJSS-2022-0012.

Phillips, Peter W.B., Jo Anne Relf-Eckstein, Graeme Jobe, and Brian Wixted. 2019. “Configuring the New Digital Landscape in Western Canadian Agriculture.” NJAS - Wageningen Journal of Life Sciences 90–91 (December). https://doi.org/10.1016/j.njas.2019.04.001.

Rose, David C., William J. Sutherland, Caroline Parker, Matt Lobley, Michael Winter, Carol Morris, Susan Twining, Charles Ffoulkes, Tatsuya Amano, and Lynn V. Dicks. 2016. “Decision Support Tools for Agriculture: Towards Effective Design and Delivery.” Agricultural Systems 149 (November):165–74. https://doi.org/10.1016/J.AGSY.2016.09.009.

Rossel, Viscarra R. A., V. I. Adamchuk, K. A. Sudduth, N. J. McKenzie, and C. Lobsey. 2011. "Proximal Soil Sensing: An Effective Approach for Soil Measurements in Space and Time." Advances in Agronomy 113 (January):243–91. https://doi.org/10.1016/B978-0-12-386473-4.00005-1.

Rotz, Sarah, Emily Duncan, Matthew Small, Janos Botschner, Rozita Dara, Ian Mosby, Mark Reed, and Evan D.G. Fraser. 2019. "The Politics of Digital Agricultural Technologies: A Preliminary Review." Sociologia Ruralis 59 (2): 203–29. https://doi.org/10.1111/soru.12233.

Rotz, Sarah, Evan Gravely, Ian Mosby, Emily Duncan, Elizabeth Finnis, Mervyn Horgan, Joseph LeBlanc, et al. 2019. "Automated Pastures and the Digital Divide: How Agricultural Technologies Are Shaping Labour and Rural Communities." Journal of Rural Studies 68 (May):112–22. https://doi.org/10.1016/j.jrurstud.2019.01.023.

Ruder, Sarah-Louise. 2019. "A Digital Agricultural Revolution: Ontario Grain Farmer Perceptions of Digital Farming and Big Data." Master's Thesis. Waterloo, Ontario: University of Waterloo.

Sadri, S, J S Famiglietti, Pan Ming, H E Beck, A Berg, and E F Wood. 2022. "FarmCan: A Physical, Statistical, and Machine Learning Model to Forecast Crop Water Deficit for Farms." Hydrology & Earth System Sciences 26 (20): 5373–90. https://doi.org/10.5194/hess-26-5373-2022.

Saifuzzaman, M, V Adamchuk, A Biswas, and N Rabe. 2021. "High-Density Proximal Soil Sensing Data and Topographic Derivatives to Characterise Field Variability." Biosystems Engineering 211:19–34. https://doi.org/10.1016/j.biosystemseng.2021.08.018.

Saifuzzaman, Md. 2020. "Optimization of Geospatial Data Modelling for Crop Production by Integrating Proximal Soil Sensing and Remote Sensing Data." Canada – Quebec, CA: McGill University (Canada). https://www.proquest.com/pqdtglobal/docview/2513263619/abstract/EFC0E39AD96B4F92PQ/49.

Sanguinetti, V. Margarita, Hanan Ishaque, Francine Nelson, Heather Ganshorn, and Guillaume Lhermie. 2024. "Protocol for a Scoping Review on Agricultural Digital Technologies in Canada Used for Crops.," April. https://doi.org/10.11575/PRISM/43238.

Sargeant, Jan M., and Annette M. O'Connor. 2020. "Scoping Reviews, Systematic Reviews, and Meta-Analysis: Applications in Veterinary Medicine." Frontiers in Veterinary Science 7 (January). https://doi.org/10.3389/FVETS.2020.00011.

Shinde, Sadanand. 2017. "Development of a Numeric On-Line Decision Support System for Crop Fertilizer Optimization." Canada – Quebec, CA: McGill University (Canada). https://www.proquest.com/pqdtglobal/docview/2503956841/abstract/EFC0E39AD96B4F92PQ/68.

Silva, George. 2018. "Feeding the World in 2050 and beyond – Part 1: Productivity Challenges." Michigan State Univeristy. https://www.canr.msu.edu/news/feeding-the-world-in-2050-and-beyond-part-1.

Soma, Tammara, and Bhoosun Nuckchady. 2021. "Communicating the Benefits and Risks of Digital Agriculture Technologies: Perspectives on the Future of Digital Agricultural Education and Training." Frontiers in Communication 6. https://doi.org/10.3389/fcomm.2021.762201.

Song, Yang, and Jinfei Wang. 2016. "Soybean Canopy Nitrogen Monitoring and Prediction Using Ground Based Multispectral Remote Sensors." In , 6389–92. https://doi.org/10.1109/IGARSS.2016.7730670.

Stanhope, Trevor. 2016. “Applications of Low-Cost Computer Vision for Agricultural Implement Feedback and Control.”

Statistics Canada. 2016. “Table 32-10-0446-01 Technologies Used on the Operation.” Census of Agriculture, 2016.

———. 2021. “Table 32-10-0379-01 Technologies Used on the Operation.” Census of Agriculture, 2021.

Steele, Dale. 2017. “Analysis of Precision Agriculture Adoption & Barriers in Western Canada: Producer Survey of Western Canada.”

Taneja, P, H K Vasava, Prasad Daggupati, and Asim Biswas. 2021. “Multi-Algorithm Comparison to Predict Soil Organic Matter and Soil Moisture Content from Cell Phone Images.” Geoderma 385. https://doi.org/10.1016/j.geoderma.2020.114863.

Tricco, Andrea C., Erin Lillie, Wasifa Zarin, Kelly K. O’Brien, Heather Colquhoun, Danielle Levac, David Moher, et al. 2018. “PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and Explanation.” Annals of Internal Medicine 169 (7): 467–73. https://doi.org/10.7326/M18-0850.

Truong, Thomas, Anh Dinh, and Khan Wahid. 2017. “An IoT Environmental Data Collection System for Fungal Detection in Crop Fields.” In 2017 IEEE 30th Canadian Conference on Electrical and Computer Engineering, 1–4. https://doi.org/10.1109/CCECE.2017.7946787.

Ulaby, F. T., R. K. Moore, and A. K. Fung. 1981. “Remote Sensing Active and Passive (Vol. 1, 456 p). Reading, MA Addison-Wesley. - References - Scientific Research Publishing.” Microwave Remote Sensing: Active and Passive. Reading, MA: Addison-Wesley. 1:456. https://www.scirp.org/reference/referencespapers?referenceid=2857687.

United Nations. 2024. “World Population Prospects 2024, Online Edition.” Department of Economic and Social Affairs, Population Division. 2024. https://population.un.org/wpp/Download/.

Vlachopoulos, O, B Leblon, J F Wang, A Haddadi, A LaRocque, and G Patterson. 2022. “Evaluation of Crop Health Status with UAS Multispectral Imagery.” IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING 15:297–308. https://doi.org/10.1109/JSTARS.2021.3132228.

Windfeld, Emma, and Guillaume Lhermie. 2022. “The Value of Canadian Agriculture: Direct, Indirect, and Induced Economic Impacts.” Frontiers in Sustainable Food Systems 6. https://www.frontiersin.org/journals/sustainable-food-systems/articles/10.3389/fsufs.2022.940968.

Wrozyna, Mason Walter. 2020. “Proximal Soil Nutrient Sensing in Croplands through Multispectral Imaging from Unmanned Aerial Vehicles (UAV) for Precision Agriculture Applications.” Canada – Ontario, CA: Trent University (Canada). https://www.proquest.com/pqdtglobal/docview/2378873472/abstract/EFC0E39AD96B4F92PQ/53.

Wulder, Michael A., David P. Roy, Volker C. Radeloff, Thomas R. Loveland, Martha C. Anderson, David M. Johnson, Sean Healey, et al. 2022. “Fifty Years of Landsat Science and Impacts.” Remote Sensing of Environment 280 (October):113195. https://doi.org/10.1016/J.RSE.2022.113195.

Yu, J, J F Wang, and B Leblon. 2021. "Evaluation of Soil Properties, Topographic Metrics, Plant Height, and Unmanned Aerial Vehicle Multispectral Imagery Using Machine Learning Methods to Estimate Canopy Nitrogen Weight in Corn." REMOTE SENSING 13 (16). https://doi.org/10.3390/rs13163105.

Zhang ChunHua, D Walters, and J M Kovacs. 2014. "Applications of Low Altitude Remote Sensing in Agriculture upon Farmers' Requests - a Case Study in Northeastern Ontario, Canada." PLoS ONE 9 (11): e112894. https://doi.org/10.1371/journal.pone.0112894.

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