Estimating Emissions from Small-Scale Diversified Agriculture: Challenges and Opportunities

University of British Columbia, Climate Solutions Scholars Final Report

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Introduction

Since the Green Revolution, agricultural production has surged, covering almost half of the world's habitable land (Ellis et al., 2010). While this expansion has increased global calorie production, it has failed to deliver food security while at the same time reshaping landscapes and communities, with implications for biodiversity, rural communities, and global emissions (Ellis and Ramankutty, 2008; Bennetzen et al., 2016). On a global scale, agricultural production has been a major source of greenhouse gas (GHG) emissions (Bennetzen et al., 2016). Presently, approximately one-quarter of global GHG emissions come from the agriculture sector (Poore, 2018). These emissions contribute to climate change, exacerbating unpredictable and extreme weather events like prolonged drought, high temperatures, and flooding, which then simultaneously impact agricultural production (Webb et al., 2020). These impacts have implications for food security across the world and for the well-being of rural and urban communities (Kim et al., 2019; Gaupp et al., 2020). Smaller-scale and diversified agroecological farming systems have been presented as key alternatives to the current food system characterized by farmland concentration, massive scales, and production for international trade (IPES-Food, 2024). Thus, there is a need to investigate the sustainability potential of small-scale agriculture in rigorous and scalable ways. Agricultural emissions calculators are one tool among many that can be used to quantify agricultural emissions and support decision-making needed to increase farm sustainability.

Emissions from agriculture have steadily risen in recent decades, a worrying trend. In 2007, Verge predicted a 50% increase in emissions from agriculture by 2030 from 2000 levels, driven by developing countries transitioning toward industrial agriculture and nitrogen fertilizer use. More recent research shows predictions like these align with Tongwane et al. (2018), identifying a more than 50% increase in African agricultural emissions between 1994 and 2014. One potential explanation for the rise in emissions is the disappearance of small-scale agroecological farms in favor of large-scale farming (IPES-Food, 2024). Mechanization, trade liberalization, and labor exits from the agriculture sector are key factors contributing to this change. While these large farms may have efficiencies in terms of output to cost, they may not necessarily adopt sustainable choices when managing their farms. On the other hand, small-scale farms have the potential to implement agroecologically beneficial practices and tend to be viewed as a natural-based solution to environmental issues, often making them a focus of sustainable policy (Ricciardi et al., 2021). However, the relationship between farm size, practices, and emissions remains far from understood (Ricciardi et al., 2021), and a lack of reliable means to measure emissions adds to the challenge of implementing effective, evidence-based policy. Understanding the relationships between farm size, crop and landscape composition, and efficiency versus emissions tradeoffs could be key to understanding whether a transition towards less consolidated and more diverse farming systems can provide a path to a sustainable agricultural sector. For this reason, the generation of accurate emissions estimates for small-scale diversified farms is extremely important. To support this transition, our team evaluated and compared several emissions calculators, primarily to inform farmers of existing tools that can support management efforts to improve their on-farm sustainability and reduce their climate impacts.

Calculating Emissions in Agriculture

Estimating GHG emissions in the agricultural sector is key to understanding the relationships between agricultural management practices and emissions generation, which will help inform climate change mitigation strategies in the sector. While these methods provide useful estimates at the national or global scale, they are not as effective for formulating focused food and emission reduction strategies for regionally specific farm management systems. Many countries have tried to adopt price-based and regulatory measures to reduce their emissions, which often include policies on land use, soil conservation, and renewable energy integration, among others (Nsabiyeze, 2024; Wauters et al., 2010; Kagata et al, 2018). Nevertheless, the scale and effectiveness of these efforts have been restricted due to the challenge of measuring emissions accurately at the local farm level (Nsabiyeze, 2024).

Secondly, dependable and transparent assessments of emissions at the local farm level can provide essential insights for producers, enabling them to monitor their GHG footprints and modify their practices to pursue sustainability goals and shift consumer preferences towards more sustainable products, which may also benefit farmers economically. Furthermore, this could help farmers comply with future international environmental regulations, including potential carbon taxes on imported agricultural goods.

Relatedly, developing and scaling out these measurements may facilitate the growth of an agricultural emissions market or the integration of agriculture into existing carbon markets, offering the incentives and infrastructure for local producers and consumers to be compensated for ecosystem services and sustainable practices. Finally, the interconnection of the agricultural sector with other sectors of the economy, along with the disproportionate impact of carbon taxes on non-agricultural sectors, could discourage sustainable economic growth across sectors especially when one sector is taxed and the other is not. Therefore, measuring emissions in the agriculture sector would pave the way for a more level playing field across sectors.

Rise of Emissions Calculators

The increasing global demand for sustainable agrifood systems combined with the Canadian government's goal to assess carbon footprints in agriculture (AAFC, 2025) has led to the development of various public and private emissions calculators for food producers. The goal of agricultural emissions calculators is to simplify complex agricultural processes into a straightforward and often static set of variables that estimate emissions. Emissions calculators take information about farm management practices and on-farm inputs (e.g. crop types, nutrient management plans, cultivation practices, etc.) and combine that information with locational (geographical location, soil type, etc.) and weather (temperature and precipitation) data to estimate GHG emissions, often reported in terms of carbon dioxide equivalents[1] (CO_2e). Stakeholders, like farmers, researchers, and policymakers, can input farm data to retrieve emissions estimates from farms. While imprecise, these calculators have greater scaling potential than in-field emissions estimation technology, such as trace gas analyzers because they are inexpensive or often free to use, offer an accessible approach for non-specialists, and can be easily understood by a general user (Richards et al., 2016).

Nearly all the calculators our team examined (see Table 1) were drawn from one of the three tier models established by the Intergovernmental Panel on Climate Change (IPCC) in 2006 and updated in 2019. Tier 1 concentrates on national inventories and emissions measurements. As the tiers progress, model complexity increases, leading to greater reliability of emissions accuracy at more localized levels. This balance between precision and complexity is fundamental to these models and their emissions estimates. Higher complexity (for instance, in Tier 3 models such as Denitrification and Decomposition - DNDC) demands much more detailed and frequent data to assess emissions locally, which can be quite a challenge for small-scale farmers. For example, one study conducted comparisons of Tier 1, 2, and 3 modeling (DNDC.vCAN) to assess nitrous oxide emissions in Canadian soils (Obi-Njoku et al. 2024). The Tier 3 modelling required extensive data, including but not limited to soil characteristics (texture, bulk density, clay content, conductivity, organic carbon, pH, field capacity, wilting points, porosity), historical daily climate data (wind speed, relative humidity, air temperature, solar radiation, precipitation), crop characteristics (biomass, yield, carbon and nitrogen concentration), and farm management records such as tillage, fertilizer application, crop rotation, planting/harvest dates (Obi-Njoku et al. 2024). This intricacy may obscure the relationship between management practices and emissions, making it difficult for farmers to grasp how their decisions influence emissions, particularly without clear, trustworthy, and consistent estimates. Conversely, simpler models often fail to capture the emissions profiles at the farm level. **Therefore, finding the right equilibrium between complexity, accuracy, and precision is essential for any scalable emissions calculator.**

These calculators are not free from limitations. Firstly, the calculators we reviewed appear to be more suited for large-scale industrial and monoculture farms, as production processes on those farms are likely to be less complex and diverse, making it easier to trace their emissions contributions throughout their operations. In contrast, small scale diversified farms are likely to have significantly heterogeneous management practices (e.g. intercropping, high levels of crop diversity within a growing season, crop rotations, multiple plantings of annuals, mix of annuals and perennials) and input choices across a growing season, which may be difficult to fully capture with these calculators. Secondly, regardless of on-farm complexities, these calculators differ significantly in their input requirements and methodologies for calculating agricultural emissions.

Our project focuses on the crucial intersection of emission estimation within the agricultural sector, where an effective and scalable tool is still under development. It offers an overview of various successful

[1] Carbon dioxide equivalent (CO_2e) is a standardized metric used to represent the global warming potential of different GHGs, in their equivalent amount of CO_2, since it is the most common GHG. Agricultural emissions are dominated by N_2O and CH_4, which have global warming potentials of 273 and 28, respectively. These GHGs can be multiplied by a conversion factor to transform them into CO_2e.

and unsuccessful pathways, discusses the challenges and drawbacks of some calculators, and showcases our contributions towards a unified calculator framework for small-scale farmers on an established platform. Additionally, it delivers accessible insights and resources for navigating this complex yet vital agricultural emissions landscape through our *Emissions Digest* and outlines a roadmap for future efforts in this field.

In our project we focused on assessing and reviewing three of the most important agricultural emissions calculators available. **Holos** is a calculator developed by Agriculture and Agri-food Canada with a specific focus on Canadian agriculture (AAFC, 2025). We reviewed **COMET Farm** which is a calculator developed by the USDA for farmers in the United States (USDA, 2019). Both rely on a mix of Tier 1 and 2 models but only have the ability to estimate emissions within their national borders because they rely on nationally specific emissions factors that have only been validated for their respective national agricultural regions. **Cool Farm Tool** was developed by the Cool Farm Alliance starting in the late 2000s as a partnership between Unilever and the University of Aberdeen, meant to support Unilever's supply chain and farmers internationally. Cool Farm Tool also uses a mix of Tier 1 and 2 methodologies and is frequently being updated to refine the methods to improve accuracy.

Table 1. Table outlining details, including the creator, focus, and IPCC Tier for each emissions calculator (i.e., Holos, COMET Farm, and Cool Farm Tool).

Calculator	*Author/Creator*	*Regional Focus*	*IPCC Tier*
Holos	Agriculture and Agri-food Canada	Canada (primarily prairies)	Tier 1 and 2
COMET Farm	United States Department of Agriculture	USA (primarily prairies and MidWest)	Tier 1 and 2
Cool Farm Tool	Cool Farm Alliance including Unilever and the University of Aberdeen	Global (primarily for industrial scale farms)	Tier 1 and 2

Climate Solutions Project

We began with four objectives: (a) adapt Holos, a Canadian-based agricultural emissions calculator, into PyHolos, a model written in Python that is designed to better suit small, diversified farms in British Columbia, Canada, while integrating the model into LiteFarm[2]; (b) compare PyHolos emissions estimates with on-farm emissions measurements taken at the UBC Farm to begin benchmarking; (c) compare and contrast outputs from Holos and PyHolos with other mainstream emissions calculators (Comet and Cool Farm); (d) create farmer-facing science communication materials to facilitate the uptake of agricultural emissions calculators. While our project evolved over the course of the term, these objectives guided our intentions. We will briefly describe this work in the section that follows, as well as explain the relevance of this experience for future agricultural emissions estimation projects.

[2] LiteFarm is an app incubated at the Centre for Sustainable Food Systems at the University of British Columbia and used by hundreds of farmers worldwide to track their management practices.

Translating Holos

Holos is originally written in the coding language of C# and is comprised of multiple 'modules' which estimate a portion of the emissions profile (i.e. direct/indirect emissions from different aspects of the agricultural production process). To adapt the Holos emissions calculator and make it better suited to the LiteFarm system – which is used by thousands of small, diversified farms globally a previous group of UBC students worked to translate one of Holos' modules focused on direct emissions from crop residue into a Python version, calling it PyHolos. Their work revealed a notable discrepancy between emissions calculated by Holos and those by PyHolos, even for the same modules, possibly due to the use of "dummy data," the incomplete translation of Holos into PyHolos or incomplete documentation, which could have resulted in an inaccurate conversion between the calculators.

Our team expanded upon this previous work to include an additional module for direct emissions from fertilizer use. Fertilizer use is linked to the production of nitrous oxide (N_2O), which is one of the primary and most potent GHGs derived from agriculture, thus making it a key lever for emissions reduction. Considering the climate impacts of on-farm fertilizer application, and given that fertilizer is a key, measurable input by farmers, this module is crucial in providing farmers with accurate emissions estimates that enable them to make management decisions that reduce emissions.

Findings from the Conversion of Holos to PyHolos

In the process of converting Holos into PyHolos, we reviewed the Holos documentation in depth, primarily focusing on crops to codify a single equation that measures direct emissions from agriculture. In particular, we incorporated the `fertilizer' component, one of the key choice variables in crop production and highly linked to agricultural emissions. We mapped all the variables related to this module and found: (a) a heavy reliance on default values and some hard-coded estimates, referenced from articles over a decade old that may not reflect the dynamic changes or disruptions in response curves due to recent climatic changes, (b) within Holos, a common and homogenous multiplier across different farms stemmed from emission factors, which do not capture the heterogeneity across farms, cultivars, and hyperlocal soil and weather relationships. This might be acceptable for national inventory calculations, where the goal is to capture aggregate emission levels, but it is not well-suited for local emission measures, and (c) despite providing similar inputs to both Holos and PyHolos, the estimates proved significantly different, hinting at incomplete documentation. These findings prompted us to reassess our objectives and consider whether translating Holos into PyHolos is the most effective method for providing emission control to small-scale farmers.

Updating PyHolos for Global Applications

Initially, our team explored the possibility of estimating emissions and enhancing the existing Holos model by using on-farm data captured at the UBC Farm. The goal was to gain insights from analysis of the data, using a non-parametric method to identify the factors influencing emissions, and using comparative statistics to examine how variations in the relationship between farm inputs and emissions occur. Our team conducted an extensive review on applying variable selection techniques and prediction models to pinpoint the key factors contributing to emissions variability, assuming access to detailed farm-level emissions data alongside input and output records. See Appendix A for methodological proposal documentation. However, we realized that while this avenue is valuable for research purposes, it may not provide actionable insights for farmers who seek clear guidance on how their practices affect emissions. Therefore, we refocused our efforts on the primary objective, which was to make emissions calculations accessible to farmers.

Getting the Right Data

To benchmark existing calculators and understand how accurately they estimated emissions, a key objective was to compare their estimates with observed emissions measured at the UBC Farm. However, this task illuminated two key challenges. Firstly, it was very difficult to find a complete, consistent data set that was interpretable across numerous years. The second was translating this data into terms that were relevant for existing agricultural emissions calculators.

Since the UBC Farm has been monitoring and collecting emissions data using various trace gas analyzers, like the LI-COR, for years (Maltais-Landry et al., 2019), we hoped to input the farm's management records into the calculators and compare the observed emissions with the estimated emissions to determine calculator accuracy in a diversified farming context. However, the data retrieval task proved to be more challenging than expected owing to the complexity of the UBC Farm record keeping system. While records have been meticulously kept for a variety of projects at the farm, the different ambitions of the projects meant there were no standard data management protocols utilized by both UBC Farm staff and UBC researchers. Here, accuracy for primary research came at the cost of usability for future work.

Second, translating the data into something relevant for the calculators was often not possible. This is partly due to the inability to interpret what information there was, but also there were often differences in the metrics of interest, i.e. what information was recorded, by whom, and in what format. This heterogeneity between farm records and calculators is a significant barrier for more widespread adoption of emissions calculators for on-farm decision information.

We believe these issues are emblematic of the challenges that exist when implementing emissions calculators beyond research farms. Diversified farms are often more labor intensive, adding a greater variety of relevant variables and management practices associated with production when compared to industrial farms. This makes it challenging to standardize a set of consistent variable inputs that will be applicable to various small-scale, diversified farm operations. This contrasts with industrial farm operations, which are more systemized, with fewer variables. For this reason, the one-size-fits-all approach of existing calculators excludes the majority of small and diversified farms. Therefore, there is a need to make calculators more adaptive to the needs of a diverse range of stakeholders.

Minimum Viable Dataset

While diversified farms are not well described by the one-size-fits-all calculators that simplify agricultural emissions to a few variables, we are hesitant to suggest that calculators become more complex. Our work on the UBC Farm showed us that adding additional variables comes with significant administrative costs, mainly in the labor of keeping additional records. Thus, a core question was to establish the minimum set of variables needed to reasonably estimate local emissions, which we called the 'minimum viable data set'.

To answer this, we investigated the types of variables used in the three selected calculators; Figure 1 shows the thematic distribution of their required inputs. Note that these are just the variables users are required to enter, not the variables the models use for emissions calculation. The variables not entered are often – though not always – generated through standard metrics (eg. COMET Farm does not require soil details because it uses default soil characteristics for the US). While this is helpful for reducing information requirements, if the local conditions differ from the assumed value, then the calculation may be flawed.

The heterogeneous calculator requirements made it challenging for us to determine which variables are most important for farmers to track. Given this heterogeneity we were unable to define a 'minimum viable data set'. Conversations with others working in this field highlighted the many details farmers are already tracking that are not currently being used in emissions calculators. For example, food safety programs, like CanadaGAP or certification designations, including Organic, require the tracking of a variety of farm management data such as amendment types, rates and dates, details on transportation (energy use), and water management, which can also be useful for calculating emissions. Additionally, we believe emissions calculators should be mindful of their complexity and data entry barriers and follow an 'enter once, use many times' approach, owing to the intense demands and time constrains farmers already face in managing their operations.

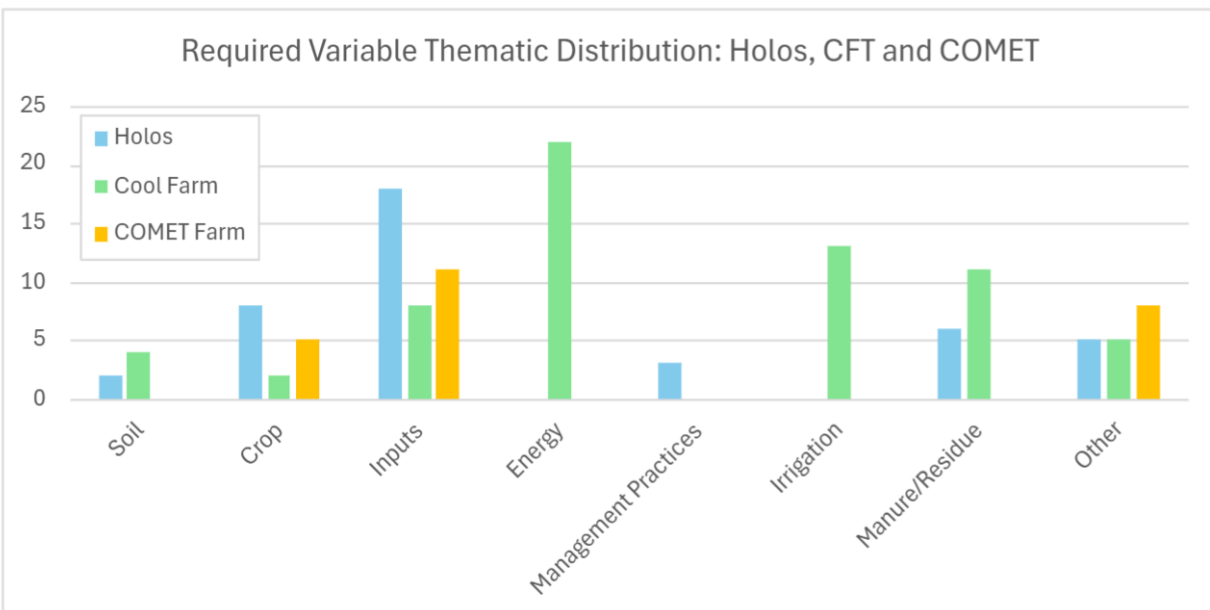

Figure 1. Thematic distribution of the required user-provided variables for emissions calculators, Holos, Cool Farm Tool and COMET Farm.

Both public and private calculators, such as Holos, Comet, and CFT, are becoming increasingly common. The objective of these calculators is to facilitate emission calculation at the farm level. However, the methodologies and inputs that they use vary substantially even within a particular group of farm management practices, e.g. fertilizer application. Additionally, calculators may rely on different tiers recommended by IPCC when it comes to measuring emissions, where the first tier is more focused towards national level calculations, masking substantial heterogeneity, whereas the third tier is more concerned with hyper-local emissions calculations. While these tiers broadly guide the trade-offs between precision and input requirements, they do not provide a clear set of standards to guide each of these tiers, which leads to significant heterogeneity among calculators even targeting the same scale (national, sub-national, farm, etc.) of emissions. We describe a case study from a farm in Alberta to provide suggestive evidence of discrepancy in emission calculation from these different calculators compared to field-level emission measurements. Overall, this makes understanding and trusting emission estimates challenging from the perspective of a farmer, even if documentation and methodology are publicly available.

Case Study: Comparing emissions estimates from various emissions calculators to measurements from an Alberta farm

Given the heterogeneity of emissions calculators and our difficulty benchmarking them with a highly diversified farm, such as the UBC Farm, we decided to use data from a large-scale research farm in Alberta, in hopes of having simpler on-farm inputs and management practices that were centralized and readily available.

A small plot trial was conducted on the Alberta research farm site to monitor N_2O emissions as they related to varying fertilization application rates throughout the 2023 and 2024 growing seasons for barley and wheat production. Three treatments of varying nitrogen (N) fertilizer rates were applied to the field crops (prescribed rate, +30%, -30%), along with a control treatment (no N fertilizer added). A long-term LI-COR trace gas analyzer measurement system was deployed in this field to obtain high temporal resolution measurements over the 2023 and 2024 growing seasons. The system was programmed to obtain two N_2O readings per chamber every hour throughout each season (May to September).

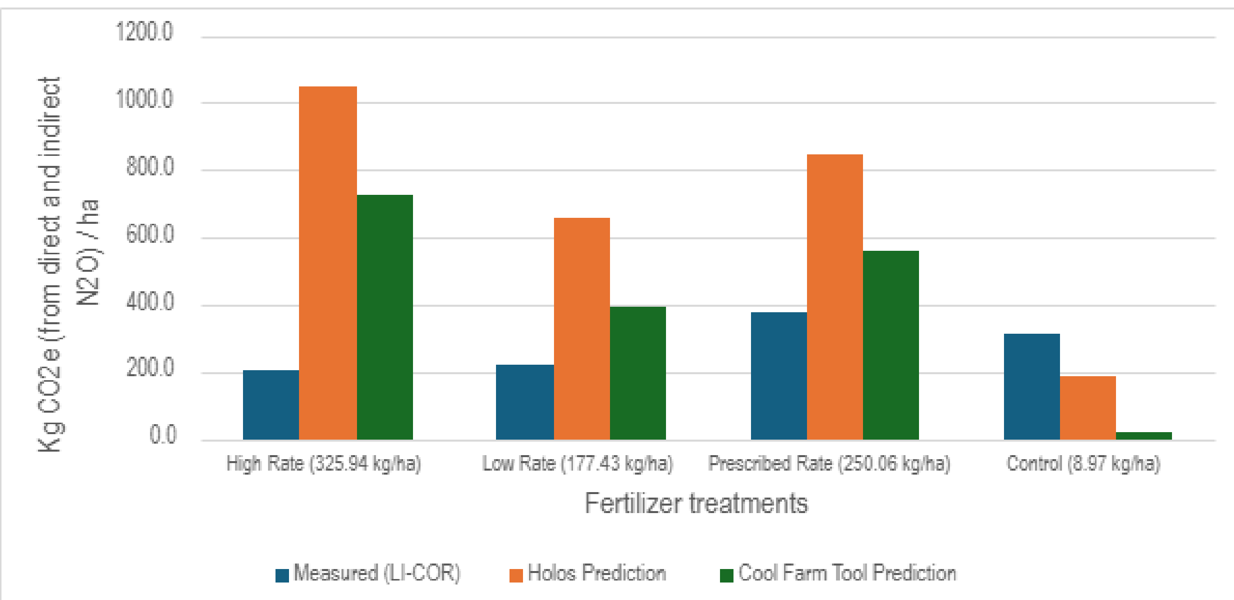

Figure 2. Comparison of emissions estimates between the Holos and Cool Farm Tool calculators and in-field measured emissions done using a LI-COR trace gas analyzer.

For this field site, all the associated on-farm management and inputs were recorded, including applied fertilizer, crop protection products (pesticides), desiccants, wet weight yield, and related field activities such as harvest and in-season operations. Moreover, environmental variables were recorded, including in-field weather station data, soil samples (suite of soil characteristics were assessed: nitrate, SOM, organic matter, etc.), and crop/grain samples throughout the season. We ran data associated with the fields of the farm where emissions were measured through the Holos and Cool Farm Tool calculators to get an estimate of emissions. The estimates were compared to measured emissions. Figure 2 shows the emissions estimates for the various calculators for four N treatments conducted in 2024. Comet Farm was excluded because it lacks required default values for regions outside of the USA.

Given the heterogeneity of the calculators' input requirements, potential reliance on default values, and varying methodologies to calculate emissions, we were not surprised to see differences in their resultant emission estimates. However, we are concerned with their poor representation of the measured emissions. While we have concerns about the generalizability of the measured emissions to other locations and cropping histories, this benchmarking underscored the over-reliance on default values when it comes to estimating emissions. Further, the calculators appeared to be more sensitive to changes in fertilizer use than any other variable, with Cool Farm Tool predicting essentially zero emissions for the control – no fertilizer – trial.

Under different conditions, the measured emissions likely would have been different, for example if the farm had been in a different part of the world. But the great disparity highlights the need for more localized emissions models. Assuming that specific locations will be well-represented by regional averages may lead to an incorrect estimation of the sustainability potential of small-scale agriculture.

This comparative work also showed that there is a greater need for improved usability. Simply entering the information into the Holos and Cool Farm Tool interfaces took around 5 person-hours per calculator. This entailed finding and extracting required data from farm management records, translating into the units required for the calculator, and looking up specific details when records were not sufficiently detailed (e.g. the brand of fertilizer was available but not the NPK ratio). Given researchers found the calculators challenging to use, calculators will need to be made more user-friendly to see widespread adoption by farmers. This is why efforts to incorporate calculators into existing farm management software are vital.

Lessons and Recommendations

The work described above established the following set of conclusions and recommendations for the second half of the project and our on-going work, and is likely to be informative for those that continue work on this project:

- **Collaboration is key:** Measuring emissions is a notoriously difficult and complex task, but our work showed that isolated efforts created counterproductive systems. It was only through working with many stakeholders that we were able to make progress on advancing the adoption of emissions calculations. In the future, scientists, like those at the UBC Farm, will have to work with calculator users to identify the key relationships and align methodologies with what is practically changeable at the farm level where emissions calculators have the potential to inform decision making.

- **Calculators must balance usability with accuracy:** Calculators focusing on small-scale diversified farms should find a balance between accuracy and usability when deciding which inputs they require farmers to provide. In other words, there is a need to have a clear and manageable minimum data requirement for reliable measure of local emissions, and to test it out, there is a need to have access to on-farm emissions data from a range of small-scale diversified farms.
- **Diversified farms need a new kind of calculator:** Our case study showed that at the very local level, and for small, diversified farms, the existing calculators do not accurately estimate emissions. Diversified farms have uniquely complex, historical, soil and metabolic processes that contribute to the difficulty of emissions estimation. Diversified farms will need new calculators that consider interactions in a novel way to accurately estimate their emissions.
- **Standardize methods but leverage flexibility for diverse users:** Emissions calculators are becoming increasingly popular and accessible. However, the proliferation of calculators means each of them has different input requirements, employs varied and often opaque methodologies, and may depend on default values that do not represent a given farm. Thus, there is a need to harmonize information requirements across different calculators as well as other reporting requirements farmers face. Building a common framework that can be used to translate information of the same subject but in different forms will reduce administrative burdens and increase the flexibility of calculators without pushing the one-size-fits-all calculator.

Some of these lessons informed us of our ongoing work, which we will describe in the next section.

On-going work

Common Farm Convention

Given the complexity and variation in input requirements across GHG calculators, our team has focused on harmonizing these requirements by contributing to the development of the Common Farm Convention (CFC), which is a standardized, extensible data framework designed to coordinate GHG emissions modelling across agricultural tools. Developed by OurSci and initially based on the internal structure of the Cool Farm Tool (CFT), CFC formalizes a core set of variables, input hierarchies, and activity records to represent farm operations consistently across systems. This foundation supports interoperable modelling workflows in areas such as crop production, livestock management, and fertilizer use.

The CFC framework is implemented as a set of machine-readable JSON schemas, making it both software-friendly and reusable. These schemas can be extended to form child conventions tailored to specific tools, systems, or organizational needs, such as the GHG modelling use case. Our team is actively collaborating with OurSci to create a GHG-specific child convention, where inputs from LiteFarm, an application designed to record farmers' management practices, are mapped to CFC in alignment with Holos and CFT calculator structures. This enables seamless data transfer from input platforms like LiteFarm to various GHG models, eliminating redundant data entry and reducing user burden.

Our team has already completed the integration of field-level crop management inputs from Holos into the CFC schema. This will soon be implemented in LiteFarm, positioning CFC as an interoperability backbone for Canadian and international users. Ultimately, this supports automated emissions reporting, scenario analysis, and comparative assessments of farm-level mitigation strategies—driven by a single, unified dataset.

Emissions Digest

As clearly shown through our work, the emissions calculator landscape is complex and challenging to navigate. Especially as measuring emissions in the agricultural sector becomes increasingly important for climate change mitigation strategies and necessary to facilitate the compensation of farmers' efforts to reduce GHGs, resources that disseminate information surrounding emissions and the various tools that exist will be key in supporting farmers in making management decisions that reduce emissions. These resources must be accessible to farmers, conveying important information in a format that is useful given their limited time and demanding priorities. To share some of the research and thinking our team has done throughout the project on these topics, we are preparing several research briefs (Appendix B) that break down information in a digestible format suited to farmers. Specifically, these briefs will focus on topics surrounding the connection between on-farm nitrogen use and GHG production, the importance of nitrogen use efficiency in relation to nitrogen loss mitigation, and the impacts of various management practices on the climate.

Research Brief 1

- This brief outlines the connections between on-farm nitrogen use, the climate, and a farmer's economic bottom line, highlighting the negative impacts of overapplication.
- To address these impacts, improving crop nitrogen use efficiency through 4R Nutrient Stewardship – Right source, **R**ight rate, **R**ight time, **R**ight place – is suggested.
- This suggestion aims to reduce greenhouse gas emissions associated with nitrogen application, while increasing farm profitability.

Research Brief 2

- This brief provides a detailed overview of the 4R Nutrient Stewardship approach, including specific examples and management practices that apply to diversified farms, specifically focusing on intensive vegetable production.
- This brief also focuses on the direct connection between on-farm nitrogen use, the climate, and a farmer's economic bottom line.

Limitations

We recognize several limitations in our work that are important to discuss: (a) we refrain from taking a position on the accuracy of any specific calculator, as our aim is not to advance emissions estimation but to simplify emissions calculators for farmers, making them easier to understand and use, and (b) this field is continually evolving, and tools along with their methodologies are likely to improve in response to the increasing demand for a sustainable food and economic system, and thus we caution readers to consider our work as an initial step in the exciting transformation of the agricultural sector.

Future of Work

We envision this work to continue in the following directions, paving the way for estimating emissions in the sector at scale.

1. Harmonization of various input requirements and the *Emissions Digest* provide the necessary path for the integration and use of existing emissions calculators into LiteFarm, a platform used by thousands of farms across the world, making emissions calculation easier for farmers.
2. The existing models need rigorous testing and benchmarking from on-farm emissions as well as testing of their underlying theoretical models through simulated data. This exercise is key for all stakeholders to trust the estimates and use this as a part of their decision-making tool.
3. While in this report we show relationship between one input use (fertilizer) and emissions, it would be key to empirically identify the impact of different management practices and input use on emissions using randomized-control trials and comparative statistics, as this will aid in identifying sustainable practices and input use.

These developments can lead to measuring the emissions from the agricultural sector, after accounting for small-scale diversified farms, and would lay the path towards pricing emissions in this space.

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Appendix

A – Variable Selection Methodology Proposal

Data for this project is sourced from several locations. Holos, Pyholos, LiteFarm, and the UBC Farm are the main sources used for this purpose. To supplement the data, Cool Farm and COMET Farm tools may also be utilized. From each source, there are a variety of variables, some of which are common to several sources, and others which are unique to certain sources. The table below displays the variables which are being considered for this modeling work.

Variable	Holos	PyHolos	Cool Farm	COMET Farm
Emissions (response variable)				
GIS Coordinates, or Lat/Long	x	x		x
Soil Texture			x	
Soil Organic matter			x	
Soil drainage			x	
Soil pH			x	
Crop	x		x	x
Year	x		x	
Planting Date	x			x
Harvesting Date	x			x
Total Area of the Field	x			
Start year of Field History	x			
Yield (wet weight)	x			x
Yield (dry weight)	x			x
Harvest amount			x	
Seed Amount				
Fertilizer Type			x	x
Manufactured			x	
Application Rate	x		x	
Application Method	x		x	
Date/Season of Application	x		x	x
Emissions inhibitor			x	
Blend	x			
Total N Applied				x
Seed Treatment - Type			x	
Seed Treatment - Application			x	
Seed Treatment - Active Ingredient (%)			x	
Organic - Amount Applied				x
Organic - Date				x
Organic - Amendment Type				x
Organic - Fresh Weight Applied				x
Organic - Total N Applied from Organic Amendment				x
Organic - Motar ratio H: C				x

Organic - Feedstock			x
Organic - Production Technology			x
Field-Perennial/Grassland - Forage for seed	x		
Field-Perennial/Grassland - Rangeland (native)	x		
Field-Perennial/Grassland - Seeded grassland	x		
Field-Perennial/Grassland - Tame grass	x		
Field-Perennial/Grassland - Tame legume	x		
Field-Perennial/Grassland - Tame mixed (grass/legume)	x		
Field-Perennial/Grassland - Number of bales	x		
Field-Perennial/Grassland - Wet Bale Weight	x		
Field-Perennial/Grassland - Moisture Content	x		
Shelterbelt - Year of Observation	x		
Shelterbelt - Row Length	x		
Shelterbelt - No. of Trees	x		
Shelterbelt - Average Circumferences	x		
Shelterbelt - Species	x		
Energy - Source		x	
Energy - Used		x	
Energy - Category		x	
Energy - Label		x	
Energy - Field - Machine Category		x	
Energy - Field - Fuel Use		x	
Energy - Water - Waste Water Volume		x	
Energy - Water - Oxygen Demand		x	
Energy - Water - Oxygen Demand Type		x	
Energy - Water - Treatment Process		x	
Energy - Processing - Allocation		x	
Energy - Processing - Type		x	
Energy - Processing - Energy Source		x	
Energy - Processing - Label		x	
Energy - Storage - Percentage Stored		x	
Energy - Storage - Store loading		x	
Energy - Storage - Unloading		x	
Energy - Storage - Storage		x	
Energy - Storage - Time in Storage		x	

Energy - Storage - Temperature Delta		x
Energy - Storage - CIPC application		x
Energy - Storage - CIPC dose		x
Intensive Tillage	x	
Reduced Tillage	x	
No Tillage	x	
Irrigation - Emissions based on volume		x
Irrigation - Start week		x
Irrigation - End week		x
Irrigation - Method		x
Irrigation - Water Source		x
Irrigation - Pumping Depth		x
Irrigation - Horizontal Distance		x
Irrigation - Power Source		x
Irrigation - Week number		x
Irrigation - Units		x
Irrigation - % of land irrigation		x
Irrigation - litre/ha		x
Irrigation - Use source and pump defaults		x
Manure - Date	x	
Manure - Type	x	
Manure - Origin	x	
Manure - Handling System	x	
Manure - Application Method	x	
Manure - Amount	x	
Residue Management		x
Carbon (in crop biomass) - Year of Change		x
Carbon (in crop biomass) - Allocation		x
Carbon (in crop biomass) - Land Use		x
Carbon (in crop biomass) - Tillage		x
Carbon (in crop biomass) - Carbon inputs		x
Carbon (in crop biomass) - Tree species		x
Carbon (in crop biomass) - Density Last Year		x
Carbon (in crop biomass) - Size Last Year		x
Carbon (in crop biomass) - Size this Year		x
Carbon (in crop biomass) - Trees planted/lost		x

Grazing - Start Date			x
Grazing - End Date			x
Grazing - Daily Utilization			x
Grazing - Rest Days			x
Grazing - Source of bales	x		
Grazing - Field	x		
Grazing - Number of Bales	x		
Grazing - Wet Bale Weight	x		
Liming - Material			x
Liming - Date of Application			x
Liming - Amount Applied			x
Transport - Mode		x	
Transport - Weight		x	
Transport - Distance		x	
Transport - Label		x	

Full metadata table located here: https://ubcca.sharepoint.com/:x:/r/teams/ubcLFS-gr-Agroecology4Climate/_layouts/15/Doc2.aspx?action=edit&sourcedoc=%7Ba5a2fae2-7170-48fc-b938-7857c2610e0a%7D&wdOrigin=TEAMS-WEB.teamsSdk_ns.rwc&wdExp=TEAMS-TREATMENT&wdhostclicktime=1733192667674&web=1

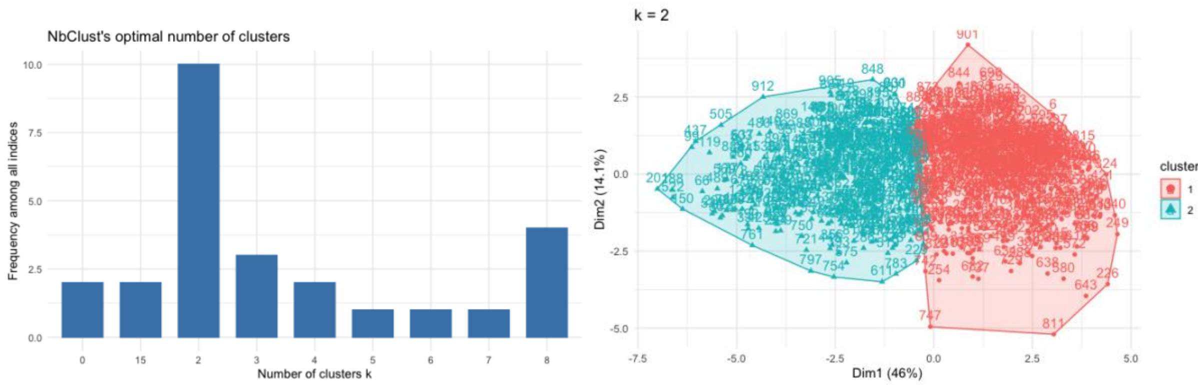
Currently the variables above are required in different amounts in each source. Cool Farm requires 66 of the total 118 variables (excluding the response variable which is only present for LiteFarm/UBC Farm). COMET Farm requires 24, and HOLOS 24 of the listed variables.

Count of Cool Farm	Count of COMET Farm	Count of Holos	Count of PyHolos
66	24	40	1

The proposed methodology and data analysis are based upon collecting empirical data and not from running the models (Holos, Comet, etc.). In the work contained in this report, we had various models available, and the equations contained within them (in the case of Holos), and a small amount of empirical data. Given that features of interest are variable between the models available, it is proposed that the data analysis consist of several components; 1) Unsupervised clustering to investigate any associations within the data or distinct groupings, 2) Principal Component Analysis (PCA) or other variable selection techniques to observe which variables are influencing the principal components for explaining GHG emissions measurements, 3) Linear Model built using information from the PCA and backwards selection.

1) Clustering

Unlike many other statistical methods, cluster analysis is typically used when there is no assumption made about the likely relationships within the data. It provides information about where associations and patterns in data exist, but not what those might be or what they mean. Several methods of determining the optimal number of clusters can be used: Gap Statistic method, Elbow method, Silhouette method, and the NbClust R package method. The clustering algorithm in R cannot handle missing values. Rows which have at least one missing value should be dropped.



Examples of clustering output. The optimal number of clusters recommended is 2 from NbClust output (left hand side), clustering visualization of k-means clustering, using k = 2.

2) Principal Components Analysis

PCA is a statistical method that transforms high-dimensional data into a lower-dimensional form while preserving the most important information. It accomplishes this by identifying new axes, called principal components, along with which the data varies the most. These components are orthogonal to each other, meaning they are uncorrelated, making them a powerful tool for dimensionality reduction. PCA analysis can be completed in R using the 'FactoMineR' package, separately for each cluster, if clustering is deemed to be beneficial/valuable for the analysis. PCA is typically done for numerical variables only, however the package 'PCAmixdata' can be used in addition because it allows for the PCA to account for categorical variables, which are important in the dataset. The PCA analysis provides a scree plot (plot showing how many PC dimensions are required to explain a certain amount of variability in the data, plots demonstrating the variables which are contributing to the top 2 PCs, and a biplot of the top 2 PCs. Considering how categorical variables may significantly contribute to the PCA analysis, it should be checked appropriately.

3. Linear Model Building

A correlation plot is checked to see if/which variables were highly correlated and based on the insight gained from the PCA analysis. If necessary, some variables are removed from the data for the modelling portion of the project. The variables that remain are considered for modeling due to their relevance to PC 1 and 2. Other variables may be removed due to correlation, or due to professional opinion from members of the research team. The following assumptions of linear regression should be checked, making sure that no violations are found (diagnostic graphs are checked).

- Predictor variables must have a linear relationship with the response variable.
- Predictor variables are not highly correlated with one another.
- Outliers and influential points are identified and removed if needed.
- Homoscedasticity and normality of the residuals is met.

4. Validation

When building the linear model, a portion of the data will be withheld and used for validation purposes. To ensure that the model predicts well on new data, we need to use data that isn't used in the training process. A simple method is to split (80:20) the dataset into two sets: train set (80% for training) and test set (20% for model evaluation) before training the model.

Improving the Bottom Line Through Climate Friendly Nitrogen Application

The Scoop on Using Nitrogen

Figure 1. Manure spreading in for potato production (photo credit: S. Smukler)

Nitrogen (N) is an essential macronutrient needed for plant growth and development. Nitrogen from fertilizers, composts, animal manures or plant residues provides nutrients that may not be readily available in soil, often increasing yield and farm profitability (Figure 1). Despite over 50 years of agricultural research to improve the use of N, globally crops typically utilize 50-80% of the N that farmers apply, with the rest lost via microbe consumption, leaching, runoff, or off-gassing. It is challenging to synchronize the uptake of N in its plant-available form *when and where the crops need it*. The overapplication of N increases financial costs, degrades soil, water, and air quality, and acts as a significant source of agricultural greenhouse gas (GHG) emissions. Improving the efficiency of N fertilizers by utilizing management practices that maximize N uptake by the crop and minimize the loss of N from agricultural lands can benefit the farm's bottom line, while helping the environment.

What is Nitrogen Use Efficiency?

Nitrogen use efficiency (NUE) estimates how much of the applied N actually contributes to crop production. Low NUE values often indicate inefficient plant uptake, while very high NUE suggests plants are depleting soil N. NUE estimates are based on ratios of N content of the source applied, the nutrient needs of the crop, and soil characteristics. Strategies to calculate NUE can range from very complex, requiring multiple analyses of the crop and soil throughout the production season, to a simple estimation of the ratio of crop yield to the amount of N applied. NUE is also influenced by the form of N that is applied, the location, the timing, environmental factors, plant physiology, and soil biochemical processes. Crops mainly take up mineral forms of N, ammonium (NH_4), and nitrate (NO_3) — together we can refer to these as plant available nitrogen (PAN). Fertilizers containing N can be derived from rocks/minerals or synthetically manufactured through industrial processes or chemical reactions and are rapidly released after application as PAN. Alternatively, N applied through compost, animal manure, and plant residues tend to release PAN slowly as they decompose. Effectively improving NUE requires planning for the location and timing of the release of PAN, ideally accounting for all its sources.

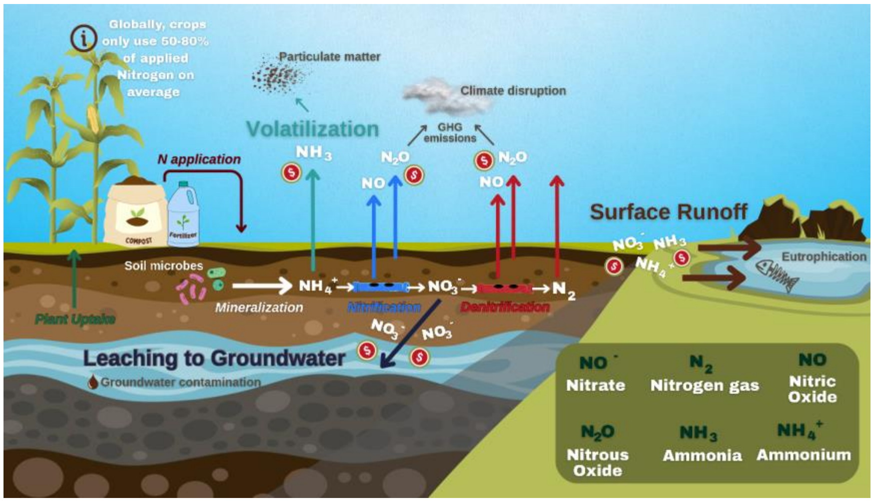


Figure 2. *Diagram showing the most common pathways where nitrogen is lost to the environment.*

How is Nitrogen Lost to the Environment?

When N is applied to soil, regardless of its source, it is susceptible to losses to the environment (Figure 2). These losses are generally controlled by microbial activity and environmental conditions that affect them, such as temperature and moisture. N that is applied without soil incorporation is especially prone to being lost. N in all its forms is susceptible to surface runoff through erosion and leaching, which can contaminate groundwater, particularly as NO_3, which is water soluble. Additionally, N can be transformed to NH_4 which is then lost through volatilization of ammonia (NH_3) gas. As N is transformed through nitrification from NH_4 to NO_3, it is lost to the atmosphere. NO_3 can then be converted into N_2O and nitrogen gas (N_2). Critically, N_2O is a GHG 273 times as powerful as carbon dioxide and is one of the primary sources of emissions from agriculture, highlighting its impact on the climate system.

Improving NUE and Results through 4R Nitrogen Management

Improving NUE can help mitigate N loss and increase crop yields and profits, as NUE is directly linked to the conversion of available N into plant biomass. This can be done by using a 4R Nutrient Stewardship approach: **R**ight source, **R**ight rate, **R**ight time, **R**ight place (see *4R Nutrient Stewardship to Reduce Nitrogen Use and Greenhouse Gas Emissions, While Improving Farm Profitability* for details). Using the 4R approach has been shown to increase NUE across a wide range of agricultural systems. In a study evaluating NUE on a national scale across the United States, researchers found that a simulated 20% increase in NUE would result in an increase in **farmer profits of 1.6% per year**. Considering a sizable amount of applied N is lost to the environment, reducing initial application rate is economically beneficial as well. In a study based in Ontario, researchers used a representative corn farm model to calculate that reducing the N application rate from 170 to 150 kg N ha^{-1} would result in an **increase in net return of \$22.32–\$36.25 $ha^{-1}yr^{-1}$.**

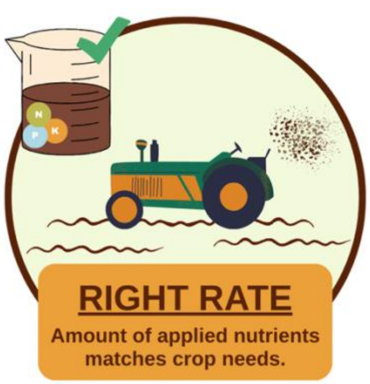
Key Takeaways

On both a global and local scale, farmers are currently overapplying N. This overapplication not only affects a farm's bottom line but also has impacts on the environment and climate. To address these issues, efforts should concentrate on improving NUE, which will simultaneously increase farm profitability and reduce agricultural GHG emissions.

4R Nutrient Stewardship to Reduce Nitrogen Use and Greenhouse Gas Emissions, While Improving Farm Profitability

The 4R Nutrient Stewardship framework **— R**ight source, **R**ight rate, **R**ight time, and **R**ight place — provides an approach to improving nitrogen use efficiency (NUE) while optimizing yield and minimizing environmental impacts. By minimizing nitrogen (N) losses, it also serves as an effective emissions reduction strategy; in Canada, widespread adoption of these practices could reduce GHG emissions by 6.3 million Tonnes of CO_2 equivalents annually by 2030, contributing 3% toward the national Paris Accord target. While applicable across diverse agricultural settings, this brief focuses on implementing the 4R's in intensive vegetable production systems, where overapplication and N loss are common owing to shallow-rooted crops, high N demand over short periods, and frequent irrigation, which can contribute to significant nitrate (NO_3^-) leaching. Further contributing to these issues, limited data on nutrient application rates reduces capacity to make informed recommendations that maximize yields, while minimizing environmental losses. For these reasons, 4R Nutrient Stewardship is a key approach for minimizing N loss to improve farm profitability and mitigate GHG emissions.

Choosing the right nutrient sources is essential to: (1) ensure N is in plant-available forms, (2) match crop nutrient requirements, and (3) complement existing nutrient sources. Organic sources, like manures, plant residues, and compost, release nutrients slowly; waste products like manure are typically inexpensive and may also help lower costs. Incorporating leguminous cover crops (clover, peas, etc.) enhances biological N fixation, builds organic matter content, and promotes microbial communities. Cover crops also reduce erosion and nutrient leaching, all of which can contribute to the improvement of NUE. This can be directly translated into increased yields, as seen in a multi-year processing tomato study based in Ontario. Plots with cover crops consistently outperformed bare control plots in yield, with **partial profit margins up to $1,320/ha with oilseed radish** and **$960/ha with oats**. Growing leguminous cash crops (lentils, chickpeas, etc.) or forage crops (alfalfa, vetch, etc.) can also achieve these outcomes, while acting as a source of profit. Alternatively, investing in nitrification inhibitors or slow-release fertilizers can improve NUE, while **reducing N_2O emissions by 20-40% per unit of N applied**.



Optimizing nutrient application rates through nutrient management planning helps prevent overuse, reduce environmental harm, and sustain or improve yields. Effective planning aligns application rates with crop requirements and accounts for existing nutrient sources, including those from previous crop residues. On top of this, timely, affordable, and accurate nutrient testing, especially annual soil tests, is key to informed decision-making and avoiding overapplication. In cucurbits, for example, excess N can promote vegetative growth at the expense of fruit development, reducing marketable yield. A multi-site study on butternut squash in southwestern Ontario found that at **64% of field sites**, the **provincially recommended N rates**

were unnecessarily high – failing to improve yields and adding avoidable input costs. Similar results were found in a study conducted in the Lower Mainland of British Columbia on potato production, where a **cost-benefit analysis reported that the increase in yield from 90 to 120 kg N ha^{-1} did not significantly outweigh the additional fertilizer costs**. However, in this case, provincial guidelines of **70 kg N ha^{-1}** are often surpassed by farmers in the area, with application rates reported as high as **112 kg N ha^{-1}.** These results underscore the economic and agronomic importance of adjusting fertilizer rates to actual crop and soil conditions prior to application to avoid waste, additional costs, and in some cases, yield penalties. Without this information, growers are likely to overapply N to combat the risks of lower yield.

Timing N applications to align with crop demands over the growing season reduces N losses and maximizes uptake, improving NUE. Utilizing tools, like sensors, field observations, tissue testing, and forecasting models can facilitate dynamic responses to weather and guide split applications to better align with plant needs. In a modeling study focused on corn in Ontario, findings suggested that **split N application** with rate adjustments may **increase profits between 15-19% in dry conditions** and **between 1-15% in wet conditions**, while reducing nitrate leaching and indirect N_2O emissions.

Nutrient placement affects both crop uptake and N losses. Applying N near the root zone during key growth stages—through incorporation, injection, banding, or side-dressing—can enhance NUE and reduce volatilization and leaching. However, these methods have trade-offs: surface-applications increase NH_3 volatilization and indirect N_2O emissions, while injection may raise direct N_2O emissions by creating denitrification hotspots. Subsurface placement is often recommended, but its impact on emissions is uncertain. As such, investing in new systems may not be cost-effective if farms have suitable application methods. Instead, focusing on **localized placement,** like shallow incorporation or banding near the root zone, can improve NUE while minimizing emissions.

Key Takeaways

Considering the climate impacts of on-farm N application and that nutrient amendments are a measurable input by farmers, targeting N through 4R Stewardship is an effective strategy to reduce GHG emissions, while improving a farm's financial bottom line.

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