



On-farm Precision Experimentation in Western Canada: A Case Study Focused on Adoption, Challenges, and Practical Results

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Abstract.

On-farm experimentation can improve management practices by providing localized results that align with the environment, genetics, and management of a specific field, farm, or region. However, operational challenges, such as the time required to implement and harvest an experiment and analyze results, can be barriers to adoption. The technology available in modern machinery (e.g., variable-rate technology and yield monitors) can overcome operational challenges by autonomously implementing and recording trial yields, an approach known as on-farm precision experimentation (OFPE). This study implemented OFPE across multiple farms in Central Alberta, Canada, to assess its operational viability, farmer acceptance, and agronomic outcomes. Over two growing seasons (2024-2025), 14 trials were conducted with partner producers: nine evaluated both nitrogen and wheat seeding rates, four evaluated only wheat seeding rates, and one evaluated only nitrogen rates in wheat. A questionnaire collected the necessary information to design the trials (e.g., standard seeding and fertilizer rates, field boundary file, wheat variety, equipment model and brand). This information was used in conjunction with the Data Intensive Farm Management platform (difm.farm) to generate Latin-square checkerboard trial designs, which were uploaded to farmers' machinery monitors. All trials were at least 61 m long, with the width varying by machinery size. The results were analyzed from two perspectives: acceptance and feedback from farmers and agronomists regarding OFPE, and crop response to the trials. Implementation was generally successful; however, challenges included uploading prescription files to the machinery displays, mid-season equipment changes, and communication issues that led to incorrect trial implementations in some fields. Farmer and agronomist acceptance was strong, with a Net Promoter Score of 87.5

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and a mean process-ease rating of 4.0 out of 5, although qualitative feedback revealed recurring friction with technology integration during implementation. Across both seasons, approximately 61% of analyses indicated that input rates below the producer's status quo maximized partial profit, while 26% suggested that higher rates would have been more profitable; the remaining 13% found no practical differences between the optimal and the producer's status quo rates. Overall, the first two years of OFPE implementation in Alberta were successful, with farmers interested in continuing and expanding the project. The plan for 2026 is to scale to 25 trials in Alberta and 5 trials in Saskatchewan.

Keywords.

Variable-rate technology, Nitrogen management, Seeding rate optimization, Site-specific crop management

Introduction

Global fertilizer markets have experienced price volatility since 2021, affected by energy price shocks and trade disruptions. While global fertilizer demand proved relatively resilient during this period, the impact on farm profitability was uneven across regions (Vos et al., 2025), indicating that the industry must focus on improving management practices that maximize return on investment. In parallel, governments in several jurisdictions, including Canada, the European Union, and Uruguay, have adopted policy targets to reduce nitrous oxide emissions from agriculture as part of broader climate commitments. Nitrogen fertilization optimization has been identified as an opportunity for agriculture to contribute to these reduction targets without compromising crop production (Cui et al., 2024; Li et al., 2025; Environment and Climate Change Canada, 2022). Meeting both pressures, protecting profit margins under volatile input costs while contributing to policy-driven emissions goals, requires field-level experimentation that provides accurate decision-making information based on specific soils, climate, and management of individual farms rather than generalized regional guidelines.

On-farm experimentation (OFE) has long served the need to produce agronomic evidence under commercial field conditions rather than in small-plot research-station trials (Tanaka et al., 2026). On-farm data are often collected using strip designs that disregard spatial autocorrelation, violate the statistical assumption of independence, and lack adequate replication, resulting in potential bias in statistical analyses and posing a risk to accurate management decisions (Legendre et al., 2004). Traditional small-plot and strip trials remain valuable, but they are costly and time-consuming to implement and analyze at the scale required to generate locally relevant, defensible recommendations across entire fields.

Modern machinery that combines yield monitoring, automated guidance, and variable-rate control has made it practical to apply treatments and record yield responses without interrupting normal field operations. This capability supports the development of on-farm precision experimentation (OFPE): trials in which existing equipment implements treatments and captures spatially explicit yield data at an operational scale (Bullock et al., 2019). OFPE has since been applied across diverse crops and regions, including the Data-Intensive Farm Management (DIFM) project at the University of Illinois, USA (Bullock et al., 2019); organic grain systems in Manitoba and Montana (Loewen & Maxwell, 2024); wheat and barley in Argentina (de Lara et al., 2023); and grain cropping in Australia (Colaço et al., 2025). Regardless of the framework adopted or location, the goal of OFPE is consistent: to give farmers and agronomists confidence that management recommendations are grounded in local, up-to-date, field- or region-specific data.

Therefore, the main objective of this study was to implement OFPE across multiple farms in Central Alberta, Canada, to assess its operational viability, farmer acceptance, and agronomic outcomes.

Methodology

OFPE trials, as per the DIFM methodology (Bullock et al., 2019), were implemented in 14 wheat (*Triticum aestivum*) fields located in Central Alberta (the region between Calgary, AB and Edmonton, AB). Figure 1 presents the spatio-temporal distribution of the implemented trials. Agricultural Regions of Alberta Soil Inventory Database (AGRASID version 4.1; Alberta Agriculture and Irrigation, n.d.), a soil survey provided by the Alberta Government at a scale of 1:100,000, was used to identify soil great group classification for each field according to the Canadian Soil Information Service (CanSIS 3rd Edition; Soil Classification Working Group, 1998). In addition, selected attributes [i.e., clay (%), organic carbon (%), pH, Cation Exchange Capacity (CEC; Meq/100g)] from soil sampling analyses available through the CanSIS database were obtained for each field.

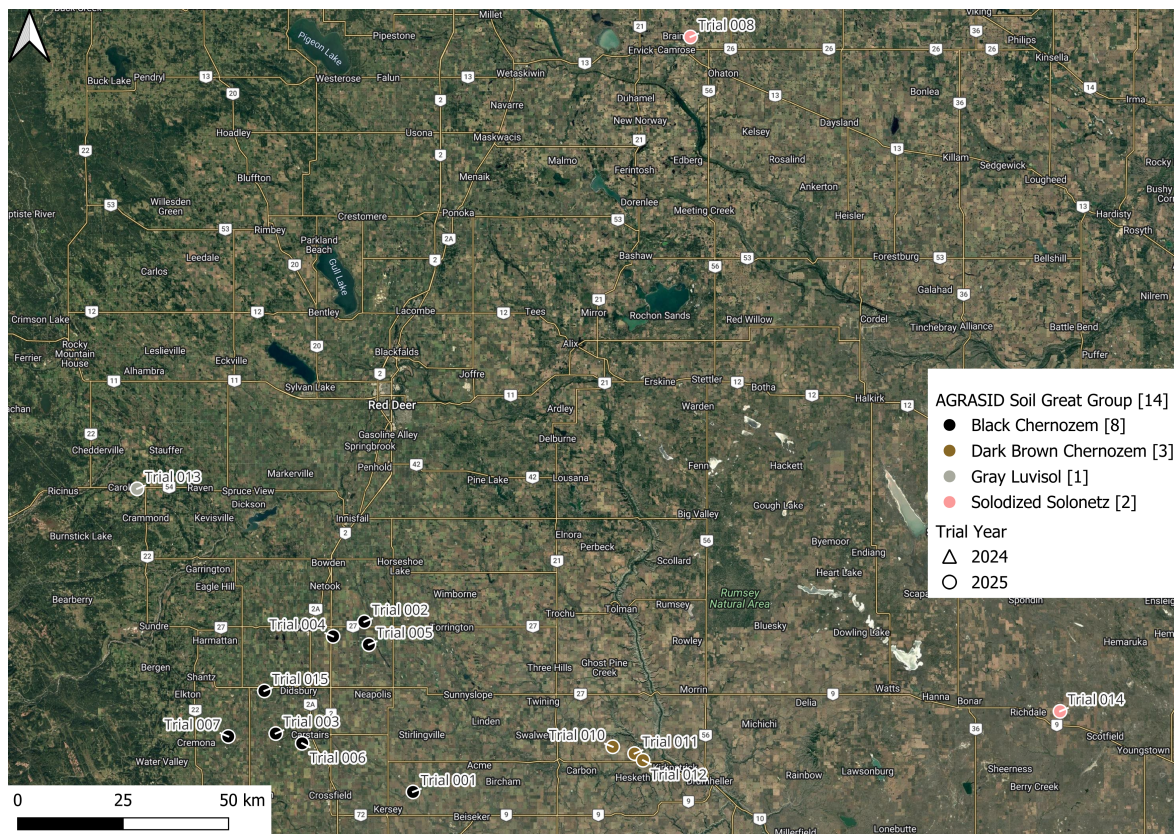


Fig 1. Trial locations, Agricultural Regions of Alberta Soil Inventory Database soil great groups, and trial year across the 2024/25 network.

High-resolution atmospheric, soil, and spatial variables were obtained from the ERA5-Land reanalysis dataset (Copernicus Climate Change Service, 2019). Moisture availability was characterized using monthly precipitation totals (April-August) alongside aggregate accumulation across the growing season and grain-filling periods. Baseline thermal conditions were captured via mean air temperatures during the growing season and grain-filling stages, maximum air temperatures during grain filling, and upper-layer soil temperatures at seeding. To evaluate crop timing and physiological stress, cumulative growing degree days (CGDD; base temperature of 0°C, seed and harvest days as reported by producers), May frost days (temperature < 0°C), and grain-filling heat days (temperature > 30°C) were incorporated.

Prior to trial development, baseline agronomic, operational, and technological variables were collected from partner producer/agronomist through a questionnaire. Farm-level metadata included historical four-year crop rotations, primary tillage practices, wheat variety, standard seeding and fertilizer rates, and baseline fertilizer management practices (urea rates, complementary nutrient rates, and placement methods). To evaluate precision equipment

capabilities, variable-rate application capabilities alongside detailed seeder and combine specifications, including brand, model, implement widths, monitor systems, Global Navigation Satellite Systems (GNSS) differential correction accuracy, and operational headland passes, were collected.

Using the information provided in the questionnaire, the difm.farm platform was used to create the trials. In this process, some trials varied both nitrogen and seed; others varied only seed or only nitrogen, a choice based on the farmer's or agronomist's perspective and equipment capabilities. To maximize data value, treatment levels were defined based on field size and number of replicates. Trials followed a Latin-square checkerboard design generated within the DIFM platform. All trial strips were at least 61 m in length, with strip width determined by the width of each producer's seeding and application equipment. For fields where seed and nitrogen trials were conducted together, associations of high seeding rates with high nitrogen rates, or of low seeding rates with low nitrogen rates, were avoided to mitigate economic risks, resulting in incomplete factorial designs.

After the trials were generated within the DIFM platform, they were analyzed and confirmed by the farmer. Upon the farmer's approval, SMS Advanced software (Version 25; Ag Leader Technology, Ames, IA, USA) was used to convert the data package into a format compatible with the farmer's equipment prescription map, including guidance lines for both seeding and harvesting. In some instances, when equipment was equipped with telematics systems, these were used to facilitate the data transfer process, allowing the prescription file and guidance lines to be sent directly to the machine's display.

Consistent communication was maintained with the farmers. Once the farmers finished seeding, as-applied maps would be collected to evaluate the implementation of the trials and make any necessary adjustments to the harvest guidance lines. At harvest, farmers were advised to perform their yield monitor calibration around the field headlands before entering the plot area, and to follow the provided harvest guidance line to ensure their system would collect data within the plots.

At the end of the season, harvest monitor data and the previously collected as-applied seeding maps were imported into the difm.farm platform for analysis. For each completed trial, the platform generated field-level reports comprising the producer's status quo rate, the range of evaluated rates, and the economically optimal rate for each input (economic optimum nitrogen rate, EONR; economic optimum seeding rate, EOSR). To obtain these results, a machine learning response model (i.e., multi-arm causal forest) was fitted to the as-applied rate and yield monitor data to identify whether the resulting optimal rate varied significantly with within-field terrain covariates (elevation, slope, or both). This model was implemented internally within the difm.farm platform using the grf R package (Athey et al., 2019) and was not independently configured or validated by the authors. Finally, these platform outputs were compiled alongside site-specific soil test results, when provided by producers (organic matter, 0-15 cm; plant-available soil nitrogen, 0-30 cm), as well as the CanSIS and ERA5-Land data described at the beginning of this section.

Two derived variables were calculated to allow comparison across trials using different products and seed lots. First, the nitrogen source rate at the economic optimum was converted to an elemental nitrogen basis according to the nutrient content and, where applicable, the density of the fertilizer product used at each site. Urea 46-0-0 rates were multiplied by 0.46; liquid urea ammonium nitrate (UAN) was converted using its respective nitrogen content and density. Second, the estimated optimum plant stand (plants.m^{-2}) was calculated from the optimum seeding rate together with each seed lot's germination percentage, vigor percentage, and thousand-kernel weight (TKW). For trials T006, T007, and T014, for which the producers did not provide a seed analysis report, thousand-kernel weight was taken from the January 2026 Alberta Seed Guide variety tables for the trial's cultivar (Alberta Seed Guide, 2026). Germination and vigor are seed-lot rather than variety properties; the values used, 93% and 90%, respectively, reflect standards for certified seed and vigor levels reported in seed analysis for other trials in this network. For T010-T012, the thousand-kernel weight was taken from the Alberta Seed Guide in the same way.

Germination for these trials was set at 99%, supplied directly by the cooperating agronomist, and vigor was again assigned the standard value of 90%.

To support the evaluation of whether OFPE data can inform regional recommendations, trials were grouped into environment zones based on the dominant soil great group reported in the AGRASID at each trial location. Soil great groups represented by only one or two trials were not assigned to a zone. In addition, trials on Solodized Solonetz soils were excluded from zone assignment, as this great group occurs as an inclusion within both the Black and Dark Brown Chernozem regions and therefore cannot be assigned to a single climate-soil zone.

Two comparisons were made for each input. First, the field-level economic optimum was compared against the producer's status quo rate to quantify the direction and magnitude of any differences in the rates. Second, the economic gain associated with adopting the field-level optimum was decomposed into two components: the gain from moving from the status quo rate to a single optimized uniform rate, and the additional gain when changing from a uniform-rate to an optimum variable-rate prescription.

Two random forest specifications were evaluated using leave-one-trial-out cross-validation to assess whether zone-restricted models predicted field-level optima more accurately than models trained on the full trial network. The global model was trained on all trials with complete predictors (seed model: $n = 13$; nitrogen model: $n = 9$), with reported RMSE calculated on held-out Zone 1 predictions only. The regional model used the same procedure but restricted both training and evaluation to Zone 1 trials ($n = 7$). Both specifications used identical predictor sets and hyperparameters, isolating the effect of training scope (network-wide versus zone-restricted) on predictive accuracy. RMSE from the models was compared with a baseline RMSE, calculated as the difference between each producer's status quo rate and the platform-derived uniform economic optimum rate, to assess whether the regional model outperformed the producer's existing rate in predicting the optimum. This random forest model was implemented separately from the DIFM platform's causal forest, using Python 3.12 and scikit-learn 1.7.2, with 300 trees, maximum tree depth of 3, minimum samples per leaf of 2, "max_features" set to the square root of the predictor count, and a fixed random seed. Predictors included soil attributes (clay, organic carbon, pH, CEC), wheat class, fertilizer placement, soil great group, and antecedent ERA5-Land weather summaries preceding the trial's seeding date; the nitrogen model additionally included field organic matter and pre-season soil nitrogen.

Farmer and agronomist acceptance of OFPE was assessed using a mixed-methods approach. A structured questionnaire captured process-ease ratings on a 5-point scale (5 = very easy and 1 = very difficult) and a Net Promoter Score item measuring willingness to recommend OFPE participation. NPS responses were classified as promoters (9 - 10), passive (7 - 8), or detractors (0 - 6), following standard NPS scoring conventions. Open-ended responses on implementation challenges, technology integration, and attitudes toward regional data sharing were analyzed using reflexive thematic analysis (Braun & Clarke, 2006, 2019, 2023). Open-ended responses were recorded in writing by team members administering the questionnaire. Coding was conducted by the lead author, who was directly involved in trial implementation and farmer communication throughout the study.

Beyond the evaluations conducted within the difm.farm platform, all subsequent data analyses and figure generation were performed using QGIS (Version 3.44; QGIS Development Team, 2025) and custom Python scripts. All participating producers signed a data-sharing and participation agreement with the research team before enrollment.

Results and Discussion

The 2024/25 trial network comprised 14 completed trials across central Alberta: four in 2024 (three nitrogen-and-seeding trials and one seeding-only trial) and ten in 2025 (six nitrogen-and-seeding trials, one nitrogen-only trial, and three seeding-only trials). Note that the methodology

described 14 implemented trials. However, 15 were planned, with one seeding-only trial in 2025 (T009) excluded from the analysis due to a field-identification error (i.e., the boundary shared by the agronomist differed from the trial location chosen by the producer). Trial locations, soil Great Groups, and trial years are shown in Figure 1, and field- and trial-level characteristics are summarized in Table 1.

Table 1. Trial characterization

Trial	Nearest Town	Field Size (ha)	Year	Trial Type	Wheat Variety	Wheat Class	Main N Fertilizer Source	Fertilizer Placement	AGRASID Great Group	Analysis Zoning
001	Beiseker	136	2024	N + Seed	AAC Viewfield	CWRS	Urea (46-0-0)	Side-Banding	Black Chernozem	Zone 1: Black Chernozem
002	Olds	67	2024	N + Seed	AC Foremost	CNHR	Urea (46-0-0)	Mid-Row Banding	Black Chernozem	Zone 1: Black Chernozem
003	Carstairs	28	2024	N + Seed	CDC Pilar CL Plus	CWRS	Urea (46-0-0)	Side-Banding	Black Chernozem	Zone 1: Black Chernozem
004	Olds	93	2024	Seed only	AAC Penhold	CPSR	29.9-16-7	Side-Banding	Black Chernozem	Zone 1: Black Chernozem
005	Olds	120	2025	N + Seed	AC Foremost	CNHR	Urea (46-0-0)	Mid-Row Banding	Black Chernozem	Zone 1: Black Chernozem
006	Carstairs	48	2025	N + Seed	AAC Penhold	CPSR	Urea (46-0-0)	Side-Banding	Black Chernozem	Zone 1: Black Chernozem
007	Cremona	46	2025	N only	CS Accelerate	CPSR	Urea (46-0-0)	Side-Banding	Black Chernozem	Zone 1: Black Chernozem
008	Camrose	58	2025	N + Seed	AAC Wheatland VB	CWRS	UAN (28-0-0)	Side-Banding	Solodized Solonetz	Unzoned
010	Carbon	65	2025	Seed only	AAC Brandon	CWRS	Urea (46-0-0)	Side-Banding	Dark Brown Chernozem	Zone 2: Dark Brown Chernozem
011	Carbon	125	2025	Seed only	AAC Brandon	CWRS	Urea (46-0-0)	Side-Banding	Dark Brown Chernozem	Zone 2: Dark Brown Chernozem
012	Carbon	64	2025	Seed only	AAC Brandon	CWRS	Urea (46-0-0)	Side-Banding	Dark Brown Chernozem	Zone 2: Dark Brown Chernozem
013	Caroline	33	2025	N + Seed	AC Foremost	CNHR	Urea (46-0-0)	Side-Banding	Gray Luvisol	Unzoned
014	Richdale	252	2025	N + Seed	AAC Brandon	CWRS	Urea (46-0-0)	Side-Banding	Solodized Solonetz	Unzoned
015	Didsbury	120	2025	N + Seed	AAC Hockley	CWRS	Urea (46-0-0)	Side-Banding	Black Chernozem	Zone 1: Black Chernozem

CWRS: Canada Western Red Spring (premium high-protein milling wheat); CPSR: Canada Prairie Spring Red (medium-strength versatile baking wheat); CNHR: Canada Northern Hard Red (lower-gluten milling wheat); Row shading indicates environment zone: blue = Zone 1 (Black Chernozem), yellow = Zone 2 (Dark Brown Chernozem), gray = Unzoned.

Field sizes ranged from 28 ha (T003, Carstairs) to 252 ha (T014, Richdale). Eight of the fourteen fields were seeded to Canada Western Red Spring (CWRS: Canada Western Red Spring; premium high-protein milling wheat) varieties, three to Canada Northern Hard Red (CNHR: Canada Northern Hard Red; lower-gluten milling wheat), and three to Canada Prairie Spring Red (CPSR: Canada Prairie Spring Red; medium-strength versatile baking wheat). The main source of nitrogen was applied as urea (46-0-0) in twelve of the fourteen fields; T004 used a 29.9-16-7

custom blend, and T008 used UAN (28-0-0). Side-banding was the predominant placement method, with mid-row banding used at T002 and T005. Note that the use of different varieties, wheat classes, fertilizer sources, and placement can be confounding factors in the analysis when aggregating this dataset.

Fields were grouped into two zones for the regional recommendation. Eight locations on Black Chernozem soils (T001-T007, T015) were grouped as Zone 1, and the three Dark Brown Chernozem trials near Carbon (T010-T012) as Zone 2. The remaining three fields (T008 and T014 on Solodized Solonetz, and T013 on Gray Luvisol) were not assigned to a zone. T008 and T014 share a soil great group but differ in organic matter content and in the growing-season weather experienced at their respective locations. T013 is the only trial on Gray Luvisol. In both cases, the available representation was judged insufficient to characterize a zone at this stage.

Figure 2 compares the 1991-2020 climate normal with the 2024 and 2025 growing seasons for a location at the center of the Zone 1 trial cluster. The 2024 season was warmer and drier than normal through the grain-filling window (July-August), with above-normal maximum temperatures and below-normal July precipitation. This combination may have contributed to lower yields in 2024 and, in turn, to the higher residual plant-available soil nitrogen measured in several 2025 fields (Table 2). The 2025 season tracked closer to the 30-year normal for temperature, with above-normal precipitation through June and July, followed by a notably dry September that facilitated harvest. Although parts of Alberta experienced significant hail in both years, none of the producers in this network reported hail-related or any other significant yield losses.

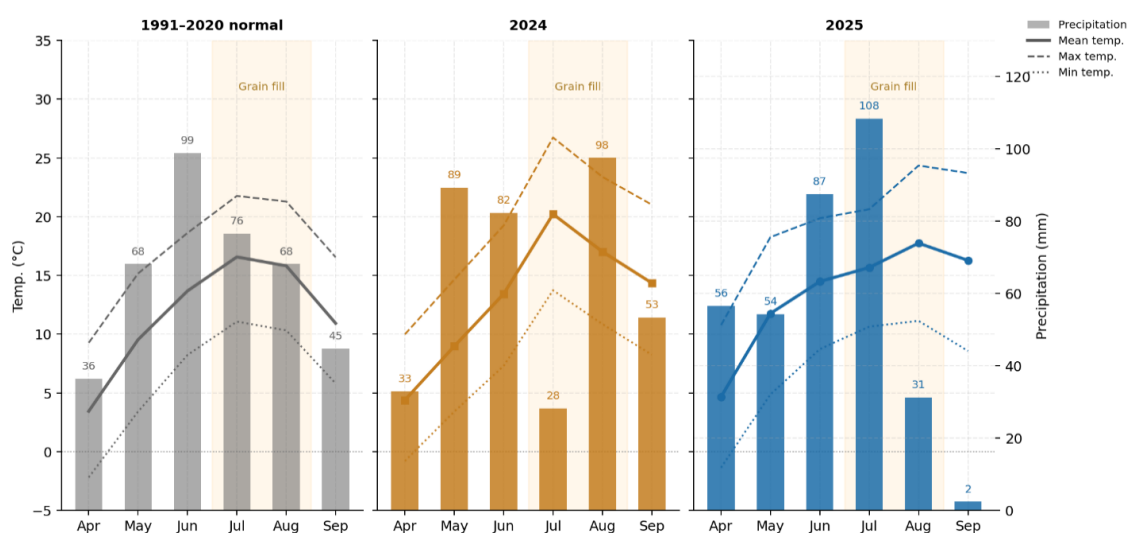


Fig 2. Growing-season temperature and precipitation for 2024 and 2025 compared with the 1991-2020 climate normal, for a location at the center of the Zone 1 trial cluster. The shaded band indicates the grain-fill window.

Nine of the ten nitrogen trials showed a relationship between the optimal rate and within-field terrain (Table 2); only T007 (Cremona) did not. As presented in Figure 3, five of the ten trials had an economic optimum below the producer's status quo rate (over-application: T001, T002, T005, T006, T015), and the other five had an optimum above status quo (under-application: T003, T007, T008, T013, T014). Correcting the uniform nitrogen rate to its field-level economic optimum nonetheless produced a positive economic impact in every trial, ranging from CAD\$7·ha⁻¹ (T008) to \$72·ha⁻¹ (T015).

T002 (Olds) and T015 (Didsbury) had the lowest plant-available soil nitrogen in the network (16 and 20 kg N·ha⁻¹, respectively), yet both showed an economic optimum below the status quo. This is counterintuitive, since lower soil nitrogen would typically support a higher, not lower, optimum rate. However, in both cases, the status quo rate was already among the highest in the network (125 and 112 kg of N·ha⁻¹), and other factors likely limited the yield response to additional nitrogen. T015, in particular, has a documented history of wild oat (*Avena fatua*) pressure and soil salinity, both of which can constrain yield response independently of nutrient supply.

Table 2. Results for the nitrogen trials from the DIFM platform

Trial	Year	Status Quo N Rate (kg N ha ⁻¹)	Range N Trial Rates (kg N ha ⁻¹)	EONR (kg N ha ⁻¹)	Total Applied N (kg N ha ⁻¹)***	EONR Varies with Topography?	Soil N 0-30 cm (kg N ha ⁻¹)	OM 0-15 cm (%)
001	2024	94	50-105	61	68	Yes	56	5.9
002	2024	125	91-135	103	113	Yes	16	7.2
003	2024	80	51-118	98	104	Yes	30	10.2
005	2025	74	52-74	64	74	Yes	45	7.4
006	2025	83	56-110	56*	62	Yes	51	7.22
007	2025	80	47-90	90**	97	No	47	7.9
008	2025	84	59-112	112**	125	Yes	48	6.4
013	2025	95	67-105	105**	123	Yes	43	-
014	2025	41	20-62	62**	67	Yes	49	3.45
015	2025	112	25-143	54	63	Yes	20	6.5

EONR: Economic Optimum Nitrogen Rate. OM: Organic Matter (0-15 cm in depth). *EONR is the same as the lowest tested rate; **EONR is the same as the highest tested rate; ***Total actual nitrogen rate applied if EONR was adopted, plus additional N from other fertilizer sources (e.g., 11-52-0).

For T008 (Camrose) and T013 (Caroline), the as-applied nitrogen rates did not adhere as closely to the original trial design as intended. Because the analysis uses as-applied rates throughout (not the original plot designs), this does not affect the validity of the per-field estimate; however, it may have reduced the precision of the rate-response relationship for these fields. In addition, no as-applied data were available for T005 (Olds); thus, the analysis was performed assuming the machinery followed the experimental design during trial implementation.

Half of the nitrogen trials (T006, T007, T008, T013, T014) had an economic optimum at the lowest or highest tested rate (Table 2). In these cases, the true economic optimum may lie outside the evaluated range, and future trials should consider widening the tested rate range in these regions.

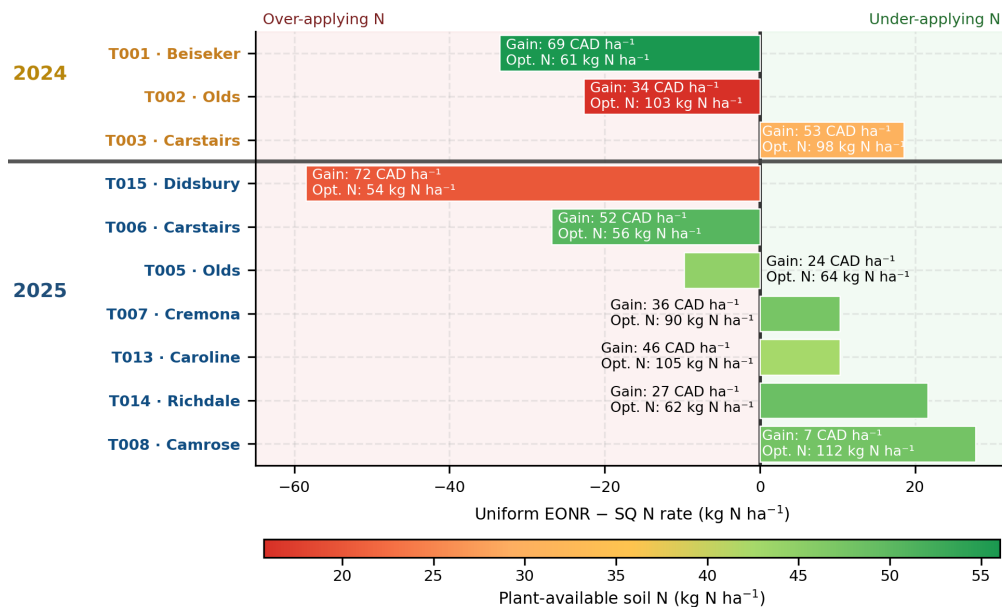


Fig 3. Field-level nitrogen rate alignment relative to the uniform economically optimum nitrogen rate (EONR). Horizontal bars show Uniform EONR minus status quo (SQ) elemental N rate (kg N·ha⁻¹) for each N-rate trial (n = 10). Negative values (left) indicate SQ above Uniform EONR; positive values (right) indicate SQ below Uniform EONR. Bar fill encodes plant-available soil N (0-30 cm sampling depth; kg N·ha⁻¹; color bar). Year groups are labeled on the vertical axis (2024, n = 3; 2025, n = 7). Text annotations report the uniform-rate economic benefit versus SQ (CAD ha⁻¹) and the Uniform EONR.

Twelve of the thirteen seeding trials showed a significant relationship between the optimal rate and within-field terrain; only T003 (Carstairs) did not (Table 3). Nine of the thirteen trials had an

economic optimum below the status quo (over-seeding: T001, T003, T005, T006, T008, T011, T012, T014, T015); three were at the status quo (T002, T004, T013); and one (T010) had an optimum above the status quo (Figure 4; Table 3).

Table 3. Results for the seeding trials from the DIFM platform

Trial	Year	Status Quo Seeding Rate (kg·ha ⁻¹)	Range Seed Trial Rates (kg·ha ⁻¹)	EOSR (kg·ha ⁻¹)	Estimated Optimum Plant Stand (pl·m ⁻²)	EOSR Varies with Topography	Soil N 0-30 cm (kg·ha ⁻¹)	OM 0-15 cm (%)
001	2024	146	113-156	113*	263	Yes	56	5.9
002	2024	170	157-191	170	355	Yes	16	7.2
003	2024	148	122-175	122*	288	No	30	10.2
004	2024	146	124-167	146	243	Yes	33	6.7
005	2025	170	159-180	159*	333	Yes	45	7.4
006	2025	146	113-146	113*	221	Yes	51	7.22
008	2025	146	112-156	123	301	Yes	48	6.4
010	2025	112	90-133	133**	305	Yes	-	-
011	2025	112	90-135	90*	205	Yes	-	-
012	2025	112	91-133	91*	208	Yes	-	-
013	2025	148	127-167	148	360	Yes	43	-
014	2025	73	52-72	62	132	Yes	49	3.45
015	2025	151	119-173	119*	217	Yes	20	6.5

EOSR: Economic Optimum Seeding Rate. OM: Organic Matter (0-15 cm in depth). *EOSR is the same as the lowest tested rate; **EOSR is the same as the highest tested rate.

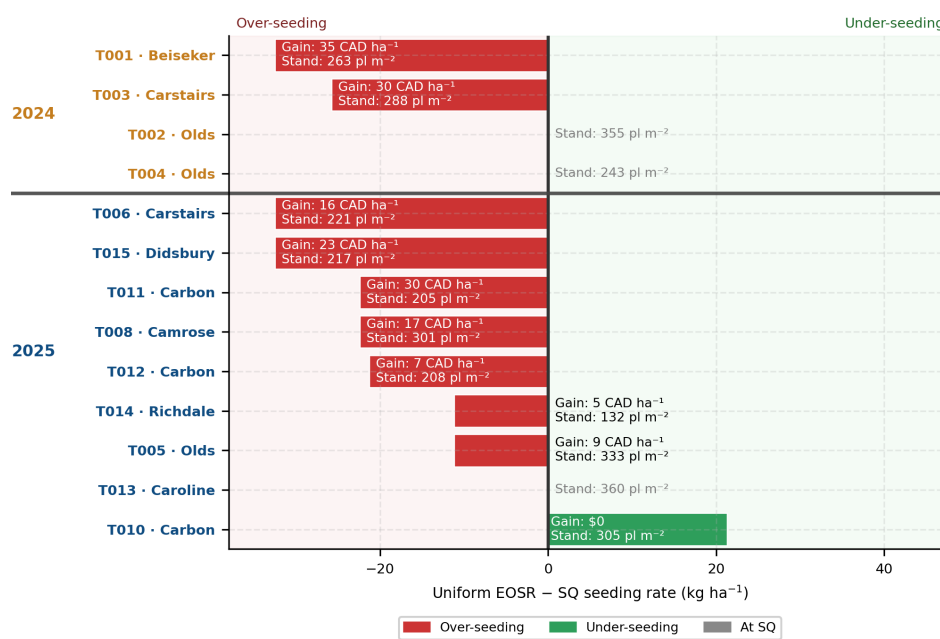


Fig 4. Field-level seed rate alignment relative to the uniform economically optimum seeding rate (EOSR). Horizontal bars show Uniform EOSR minus status quo (SQ) seed rate (kg·ha⁻¹) for each seed-rate trial (n = 13). Red bars indicate SQ above EOSR; green bars SQ below EOSR; gray bars trials at SQ. Annotations report the uniform-rate economic benefit versus SQ (CAD·ha⁻¹) and estimated plant stand at EOSR (pl·m⁻²). Trials T002, T004, and T013 are shown at SQ for seed rate (stand metrics only).

For T010 (Carbon), the platform identified 133 kg·ha⁻¹ as the economically optimal uniform seeding rate, an increase from the 112 kg·ha⁻¹ status quo (Table 3). However, upon an analysis of the raw data from the DIFM platform, the economic comparison showed no financial gain from this change, the only case in the network where the identified optimum did not correspond to a positive economic gain. This may reflect an issue with the yield-monitor data from this field,

resulting in a partial dataset for half the field. Notably, the two other Carbon-area trials within a few kilometers of T010 (T011, T012) both showed economic optima at the lowest tested rate, the opposite direction from T010's result (Table 3; Figure 4).

Eight of the thirteen seeding trials (T001, T003, T005, T006, T010, T011, T012, T015) had an economic optimum at the lowest or highest tested rate. Again, in these cases, the true economic optimum may lie outside the evaluated range, and future trials should consider widening the tested rate range in these regions.

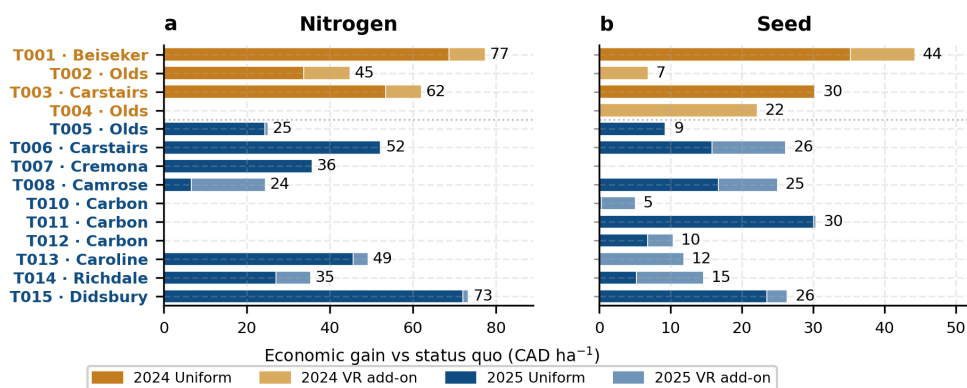


Fig 5. Economic gain from correcting each trial's rate to its field-level economic optimum for nitrogen (a) and seed (b), decomposed into the gain captured by a single optimized uniform rate (darker shade) and the additional gain available from variable-rate management beyond that uniform correction (lighter shade), by trial and year.

Figure 5 decomposes the economic gain available in each trial into two components: the gain from moving from the status quo rate to a single optimized uniform rate (darker shade), and the additional gain available from a variable-rate prescription beyond that uniform rate (lighter shade). For nitrogen, the uniform-rate gain had a median of \$53·ha⁻¹ in 2024 (n=3 trials) and \$36·ha⁻¹ in 2025 (n=7 trials). For seeding, the median uniform-rate gain was \$15·ha⁻¹ in 2024 (n=4 trials) and \$9·ha⁻¹ in 2025 (n=9 trials). In most trials, the variable-rate component added further economic value beyond the uniform-rate correction, though the relative size of this additional gain varied by trial and input.

Figure 6 evaluates whether an RF model trained on the trial network can predict optimal rates with enough accuracy to be practically useful. The benchmark used is the mean absolute difference between the DIFM-identified field-level optimum and each producer's status quo rate: a model needs to predict better than this to offer value over simply maintaining current practice. Colaço et al. (2025) found that, for machine-learning prediction of optimal nitrogen rates from on-farm trial networks, models trained on agronomically and biophysically coherent regional groupings outperformed network-wide models. Following that approach, RF models here were trained on both the full (global) dataset and the Zone 1 dataset (regional).

For optimal plant stand (Figure 6a), both the global model (RMSE = 49.3 pl·m⁻²) and the Zone 1 regional model (RMSE = 54.5 pl·m⁻²) exceed the status quo benchmark (39 pl·m⁻²), meaning that at this stage neither model outperforms the status quo as a baseline predictor. For total optimal nitrogen (Figure 6b), both the global (RMSE = 25 kg N·ha⁻¹) and regional (RMSE = 24.7 kg N·ha⁻¹) models fall marginally below the benchmark (25.5 kg N·ha⁻¹). Notably, restricting training to Zone 1 did not improve predictive accuracy for either input and yielded worse results for plant stand, the opposite of what Colaço et al. (2025) found for larger, biophysically coherent trial networks. This is likely a consequence of the reduced training set size when operating within a single zone. At the current network size, the loss of training observations due to restricting to Zone 1 outweighs any gains from biophysical coherence. This does not contradict the zoning approach recommended above. Still, it underscores that the network must first reach a scale at which zone-level training sets are large enough for the coherence benefit to materialize. Together, these results indicate that increasing network size and variability will be necessary before data-driven models can reliably support agronomic decision-making. It is also important to note that multiple

confounding factors may affect the results, including wheat class, variety, nitrogen source, and fertilizer placement.

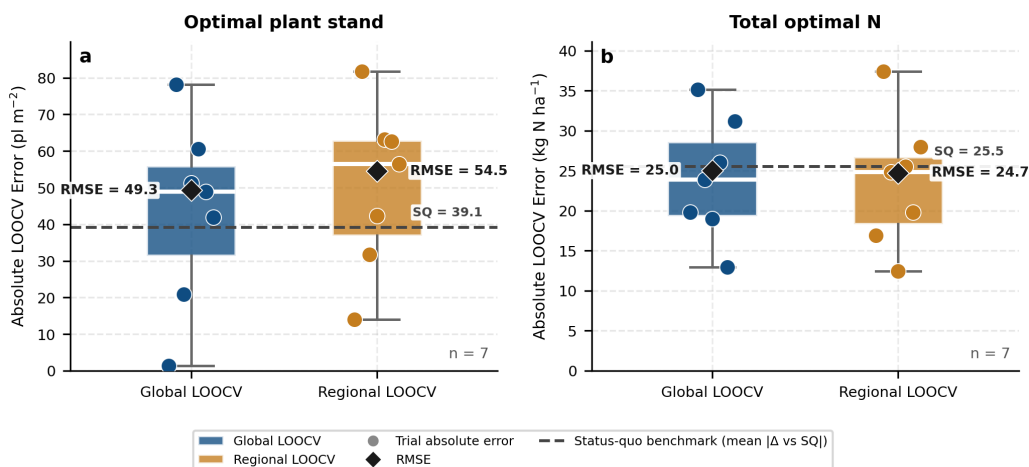


Fig 6. Leave-one-out cross-validation (LOOCV) absolute prediction error for random forest models predicting optimal plant stand (A) and total optimal nitrogen rate (B) across Zone 1 trials ($n=7$; the total number of trials is 8 in Zone 1, but one is nitrogen only and another seed only), for a global model trained on all available trials and a regional model trained within Zone 1 only. The dashed line represents the status quo benchmark: the root mean squared error calculated between the DIFM-identified field-level optimum and the producer's status quo rate. Points show individual trial errors; diamonds show RMSE. A model with practical predictive value should consistently fall below the benchmark.

As the trial network expands across zones, more advanced approaches could be applied to support more robust, zone-specific regional recommendations, such as spatially explicit per-field response modeling and meta-analytic synthesis across fields, as recently proposed by Tanaka et al. (2026). In addition, Colaço et al. (2025) suggested that adding more relatively simple trials at additional sites within an agronomically coherent zone contributes more to model performance than increasing the replication or spatial coverage of individual trials. This is a useful consideration for prioritizing future trial placement.

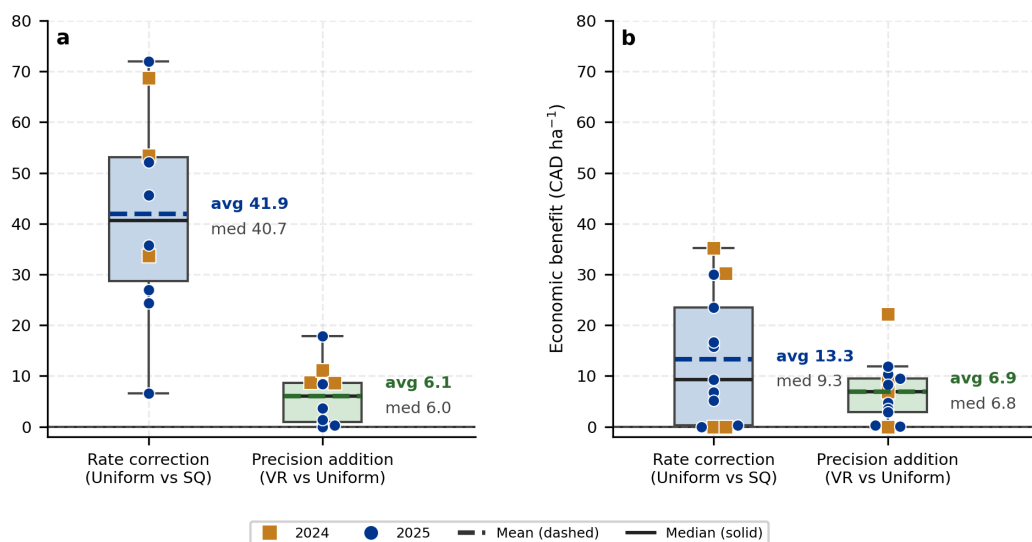


Fig 7. Distribution of rate-correction (UR versus SQ) and precision-addition (VR versus UR) economic benefits. Boxplots summarize benefits (CAD ha^{-1}) from the same source as Fig. 5. Panels display: (A) nitrogen; (B) seed. Boxes span the interquartile range (IQR); whiskers extend to the most extreme points within $1.5 \times \text{IQR}$; dashed horizontal lines indicate means; solid lines indicate medians. Individual trials are jittered (squares = 2024; circles = 2025). UR = best uniform rate; VR = variable rate relative to UR; SQ = status quo.

From a site-specific perspective, across the 23 input-by-trial combinations evaluated (10 nitrogen, 13 seeding), 21 (91%) showed a significant relationship between the optimal rate and within-field

terrain (Tables 2 and 3). This provides strong evidence that, for the great majority of fields in this network, the economically optimal input rate is not uniform across the field, supporting variable-rate management as an applicable strategy for Alberta spring wheat production under the conditions evaluated here. The economic decomposition in Figure 5 and aggregated information in Figure 7 reinforce this conclusion: in most trials, variable-rate management added economic value beyond what a single optimized uniform rate could capture. It is important to note that the analysis was performed utilizing slope and elevation alone; other spatial covariates or management zone analysis may identify different within-field variability patterns, leading to a different optimum-rate structure. The added value of variable-rate management (~\$6/ha for nitrogen and ~\$7/ha for seed; Figure 7) may not exceed typical industry costs for prescription development, data services, and variable-rate equipment.

The results from these 14 fields provided individual producers and agronomists with practical actions, indicating opportunities and strong returns on investment from improving uniform or site-specific (i.e., variable-rate) nitrogen and seeding rates (Figure 7). The responses provided by producers and agronomists to the OFPE acceptance-structured questionnaire further support this statement.

Across all respondents (n = 8; 6 farmers, 2 agronomists; a few fields belonged to more than one farmer), mean process-ease rating was 4.0 out of 5 and mean NPS was 9.4 out of 10, yielding an NPS score of 87.5 (7 promoters, 1 passive, 0 detractors). Restricted to farmer respondents alone, results were comparable (mean ease = 4.2/5, NPS score = 83.3). All six farmer respondents reported that trial participation either changed a specific input-rate decision or measurably increased their confidence in an existing one; none characterized the trial as uninformative.

These scores sit in tension with the qualitative data, which revealed consistent technical friction during implementation and an apparent adoption paradox in which perceived adoption coexists with real operational difficulty. The dominant source of friction was technology integration, spanning four distinct failure modes: display/prescription compatibility issues with proprietary hardware ("Getting the display working with the prescription was a challenge"); issues with GNSS and machinery settings that produced staggered rate transitions during seeding, described by one respondent in detail as a lag "between when the signal is coming and what it's telling the drill"; field-boundary mismatches causing equipment shutoffs; and, notably, a geographic-transferability problem in which trial software originally developed for U.S. produced processing difficulties on Alberta wheat fields. This last code is a variant of technology friction, but distinct from the others: it is a limitation of the analytical pipeline's underlying assumptions rather than of on-farm hardware, and points to adaptations the DIFM platform may need for Western Canadian conditions.

A second cluster of open-ended responses addressed regional data use, converging on two related but separable positions. First, willingness to contribute individual trial data to a shared regional dataset was consistently conditional on anonymization and an adequate network size; one respondent noted directly that, at very small sample sizes ("if you only have three producers"), individual fields become identifiable, a concern the respondent expected to diminish as participation scales. Second, and distinct from the anonymization concern, respondents offered a substantive view on how regional recommendations should be used once available: several were skeptical of extrapolating from a single trial to a regional prescription ("I wouldn't even use it... but that's how you do it, that's what they all first start"), while another argued blanket regional recommendations are appropriate primarily as a fallback for producers not currently soil testing, rather than a substitute for field-specific data. Together these responses suggest producer buy-in for OFPE's regional-recommendation goal is present but qualified, contingent on scale for privacy, and on messaging that positions aggregated recommendations as a floor rather than a replacement for on-farm data.

Several implementation-level constraints, documented independently of the questionnaire, further contextualize both the technology-integration theme and the overall results. As-applied maps for the seeding operation of T005 were lost after the machinery display malfunctioned and required

dealership replacement, an equipment failure unrelated to OFPE protocol, but illustrative of the hardware dependencies inherent to on-farm trial execution. More broadly, display and rate-controller heterogeneity across equipment brands introduced integration challenges beyond those captured in the questionnaire's technology-integration codes: platforms less common in the U.S. but standard among Canadian and European operations (e.g., Topcon on Bourgault equipment, iPad-based systems on Väderstad) required unanticipated trial-specific accommodations. Hardware integration difficulties also arose at the level of section control granularity: one trial (T008), applying nitrogen as UAN through a rate controller distinct from and with different section sizes than the seeder's rate controller, combined with a seeder lacking row-level (only section-level) control, resulted in a system that occasionally picked up rate assignments from an adjacent plot due to minor spatial misalignment. Finally, periodic miscommunication between farm operators, agronomists, and the research team, along with intermittent connectivity issues in field conditions, contributed additional operational friction not reducible to hardware alone. Collectively, these constraints indicate that technology-integration barriers identified in the qualitative data understate the full range of implementation challenges, and that scaling OFPE across a more heterogeneous framework will require processes to facilitate integration with multiple equipment brands and rate controllers.

As with any purposive sample of engaged early participants, these results likely represent an upper bound on satisfaction and adoption intent relative to a broader producer population.

Conclusion

Over its first two growing seasons, this OFPE network demonstrated that on-farm precision experimentation is operationally viable at scale using existing farm machinery, generating field-level economic and agronomic evidence across 14 wheat fields in Central Alberta. Terrain-driven variability in the economic optimum was detected in 21 of 23 (91%) input-by-trial combinations, and correcting uniform nitrogen rates to their field-level economic optimum produced a positive economic return in every trial; most seeding trials likewise favored a rate below the producer's status quo. Variable-rate management added further economic value beyond a single optimized uniform rate in most trials, though this additional gain was modest relative to typical service costs for prescription development and variable-rate equipment, a consideration that should inform how the value proposition of variable-rate adoption is communicated to producers. Preliminary random forest models restricted to Zone 1 did not yet outperform simpler network-wide models or the producer's status quo rate as predictors of the economic optimum, indicating that the trial network has not yet reached the scale needed for zone-specific regional recommendations to outperform current practice.

Farmer and agronomist acceptance of OFPE was high, with a Net Promoter Score of 87.5 and a mean process-ease rating of 4.0 out of 5, despite consistent technical friction during implementation, particularly around display and prescription-file compatibility, GNSS-related rate-transition lag, and adapting a platform originally developed for U.S. equipment and conditions to Western Canadian operations. Producers expressed conditional support for contributing data to a shared regional dataset, contingent on anonymization and adequate network size, and viewed aggregated regional recommendations as a complement to, rather than a replacement for, field-specific data. As the network expands to 25 trials in Alberta and 5 in Saskatchewan in 2026, priorities for future work include widening tested rate ranges for trials whose economic optimum fell at the edge of the evaluated range, addressing the equipment-integration barriers identified here across a more heterogeneous set of machinery brands, and building the zone-level sample sizes needed to test whether regionally coherent models can outperform field-specific status-quo practice, as observed in larger on-farm networks elsewhere.

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Appendix

The full trial and feedback questionnaires are available from the authors on request.