

Cultivar innovation: impacts of adoption and potential for adaptation

by

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B.S., University of Arkansas, 2018

M.S., University of Arkansas, 2021

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
College of Agriculture

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2025

Abstract

Chapter 1 – From Field Trials to Farm Adoption: Identifying the Productivity Effect of On-Farm Technology Adoption

Technology adoption is an important farm management decision and is frequently made using information that is unavailable to the researcher. Aside from their own experiences, producers often rely on extension services to inform their adoption decisions. Here, we propose a novel instrumental variable (IV) approach to identify the effect that a new technology, genetically modified (GM) corn, has on farm yield using instruments constructed from extension information. The proposed approach allows us to explore the degree of the endogeneity bias in estimating the impact of GM adoption on farm productivity. Candidate instruments are constructed from variety trial data to resemble information acquired by producers from university extension variety trial reports and are spatially merged with on-farm production data. We find that failure to account for the endogeneity of the adoption decision does indeed result in a substantial upward bias in the estimated productivity gains. After correcting for this bias through our IV approach, GM corn results in large on-farm yield gains of 19.6 bushels per acre. We demonstrate that variety trial data can be used to estimate the on-farm impact of a new technology, and this approach is general enough to be applied to additional contexts (i.e., technologies, crops, and/or locations).

Chapter 2 – Effects of Warming on Cool-Season Pulse Varieties in North America

Climate change is expected to have detrimental impacts on agriculture at low latitudes, some of which are already being felt. The impacts at high latitudes are less certain and are still debated. We examine the impacts of warmer temperatures at high latitudes using a novel cool-

season pulses field trial dataset that includes 87 locations in the Northern Plains of the United States and western Canada from 2001 to 2023. Using regression analysis, we identify temperature thresholds of 29°C for field peas and 30°C for lentils, beyond which yield reductions begin due to heat stress. A moderate +2°C warming severely reduces field pea and lentil yields by 15.7% and 18.9%, respectively. Projected warming scenarios are extended to estimate the impacts on test weight and protein content, finding that warming has small negative effects on test weight (-0.9% to -0.1%) and moderate positive effects on protein content (+2.5% to +5.6%). Findings suggest that even at high latitudes, breeding programs should prioritize heat resilience to mitigate the detrimental effects on yield of pulse crops under future warming scenarios.

Chapter 3 – Heterogeneous Effects of Yield and Quality for Herbicide Tolerant Lentil

Varieties

Weeds are a significant biotic stressor on crop production globally. In Canada and the United States, traits for herbicide tolerance (HT) developed through genetic engineering (GE) have been limited to crops produced for animal feed, fuel, and fiber, while crops produced for human food consumption have more limited options for weed control. Clearfield varieties are a non-GE alternative that allows producers to selectively target weeds using chemical herbicides. Using variety trial data that includes over 6,600 observations from 2001 to 2023, we quantify the effects of HT technology on lentil outcomes in western Canada and the Northern Plains of the United States. Our main findings reveal the heterogeneous effects of HT on lentil output across two important dimensions, yield and test weight. This distinction is important as HT varieties result in a yield reduction of 4.2% and an increase in test weight by 0.5%. Although there is a yield reduction overall, we find that HT improves yield by 3.4% for each day early season weed

interference. Later in the growing season when weed interference impacts lentil quality, HT increases test weight by 0.1% for each additional day of weed interference. Taken together, our results suggest that HT technology in lentils provides risk reducing benefits for production and may be a potential adaptation strategy for producers facing increased weed pressure at higher latitudes due to warmer temperatures.

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Acknowledgements

I would like to express my sincerest gratitude to Dr. Jesse Tack for his mentorship over the past four years. I am especially thankful for Jesse's patience, thoughtful criticism, and willingness to have candid conversations. Thank you to my committee members Drs. Jisang Yu, Jenny Ifft, Nathan Hendricks, and Chuck Rice for your valuable feedback on my dissertation and supporting my development as an economist.

To the faculty, staff, and graduate students in the Department of Agricultural Economics, thank you for fostering an environment that enabled me to learn and develop as a researcher, teacher, and colleague. Special thanks to Dr. Logan Britton for sharing his teaching philosophy and resources with me. Thank you to my PhD cohort for your encouragement, collaboration, and friendship.

To my parents, Debbie and Vesa, thank you both for encouraging me to work hard and be curious, and providing me with the opportunity to pursue a college degree and graduate studies. To my brother, Niko, I am grateful for our friendly sibling rivalry that has provided me with additional motivation to be a better student and researcher. To Grant, thank you for your love and support.

Dedication

This work is dedicated to my first teachers, Mom and Dad.

Preface

Agriculture faces many challenges that threaten productivity, food security, and rural livelihoods. Many emerging challenges may be offset by producers adopting new technologies and practices that result in productivity gains. *Cultivar innovation: impacts of adoption and potential for adaptation* is comprised of three chapters that use production economics to provide insights into these challenges and avenues for adaptation. Each chapter explores topics related to technology adoption, farm management, and environmental stress by leveraging different sources of variety trial data to examine the effects of cultivar innovation (i.e., crop improvement through breeding) on agricultural output. A brief overview is given for each chapter in the paragraphs below.

Chapter 1 focuses on a long-standing empirical issue in the agricultural economics literature, specifically, accounting for endogeneity in the technology adoption decision. I developed a novel instrumental variable (IV) approach to identify the effect that a technology, genetically modified (GM) corn, has on farm yield using instruments constructed from extension information. Candidate instruments were constructed from variety trial data to resemble information acquired by producers from university extension variety trial reports and were spatially merged with on-farm production data. I found that failure to account for the endogeneity of the adoption decision resulted in a substantial upward bias of 24% in the estimated productivity gains. After correcting for this bias through my IV approach, GM corn resulted in large on-farm yield gains of 19.6 bushels per acre. This essay demonstrates that variety trial data can be used to estimate the on-farm impact of a new technology, and my approach is general enough to be applied to additional contexts (i.e., technologies, crops, and/or locations).

Chapter 2 provides insights into the impacts of climate change on agricultural production at high latitudes, a topic that is still debated in the literature. Specifically, I examined the impacts of warmer temperatures in the Northern Plains of the United States and western Canada using a novel cool-season pulses field trial dataset. I constructed this dataset using publicly available field trial reports from 2001 to 2023. Pulses are typically characterized as being resilient to heat stress, however, I found that moderate +2°C warming severely reduces field pea and lentil yield by 15.7% and 18.9%, respectively. Projected warming scenarios were extended to estimate the impacts on two important quality measures: test weight and protein content. I found that warming has small negative effects on test weight (-0.9% to -0.1%) and modest positive effects on protein content (+2.5% to +5.6%). These findings suggest that opportunities to offset the negative yield impacts may exist through offering price premiums for pulses with elevated protein content. However, breeding programs should prioritize heat resilience to mitigate detrimental effects on yield of pulse crops under future warming scenarios even at high latitudes.

In the agricultural production literature, limited attention has been devoted to non-GM crop-trait technologies despite being adopted by producers for weed control in some production systems. Chapter 3 investigates the effects of a non-GM technology, Clearfield, on lentil yield and test weight in western Canada and the Northern Plains of the United States. My main findings reveal that herbicide tolerant (HT) varieties result in a yield reduction of 4.2% and an increase in test weight by 0.5%. Although there was a yield reduction overall, I found that HT improved yield by 3.4% for each day of early season weed interference. Later in the growing season when weed interference impacts lentil quality, HT increased test weight by 0.1% for each day of weed interference. Taken together, these results suggest that HT technology in lentils

provides risk reducing benefits for production and may be a potential adaptation strategy for producers facing increased weed pressure at higher latitudes due to warmer temperatures.

Chapter 1 - From Field Trials to Farm Adoption: Identifying the Productivity Effect of On-Farm Technology Adoption

1.1 Introduction

Technological innovation has constantly altered the agricultural landscape (Griliches 1960; Lichtenberg 1989; Olmstead and Rhode 2011) and is a major driver of the large gains in on-farm productivity over the past century (Pardey and Alston 2021). Many argue that innovation can aid current and future challenges facing agriculture such as adapting to climate change and ensuring global food security (Cassman 1999; Smit and Skinner 2002; Godfray et al. 2010; Ray et al. 2013). Technology generation alone does not result in efficiency gains; rather, changes to production occur when producers decide to adopt innovative technologies. Thus, technology adoption is an important farm management decision for all producers regardless of scale or scope and is a cornerstone of the agricultural economics literature (Feder, Just and Zilberman 1985; Sunding and Zilberman 2001).

A critical challenge of analyzing technology adoption is that it is an ever-present, evolving, and dynamic decision-making process based on information that is often unavailable to the researcher (Besley and Case 1993; Foster and Rosenzweig 2010; Perry, Hennessy and Moschini 2022). Prior to the adoption decision, a producer must assess the expected benefit of that new technology and use that information to make a decision *ex ante* to knowledge of its actual on-farm impact (Foster and Rosenzweig 1995; Barkley and Porter 1996; Barkley 2024). Another complicating factor is that some forms of technology can be easily experimented with on-farm at a low cost while others require substantial up-front acquisition and/or learning costs. Either way, the decision maker must collect information, assess its credibility, and form an expectation of the on-farm impacts.

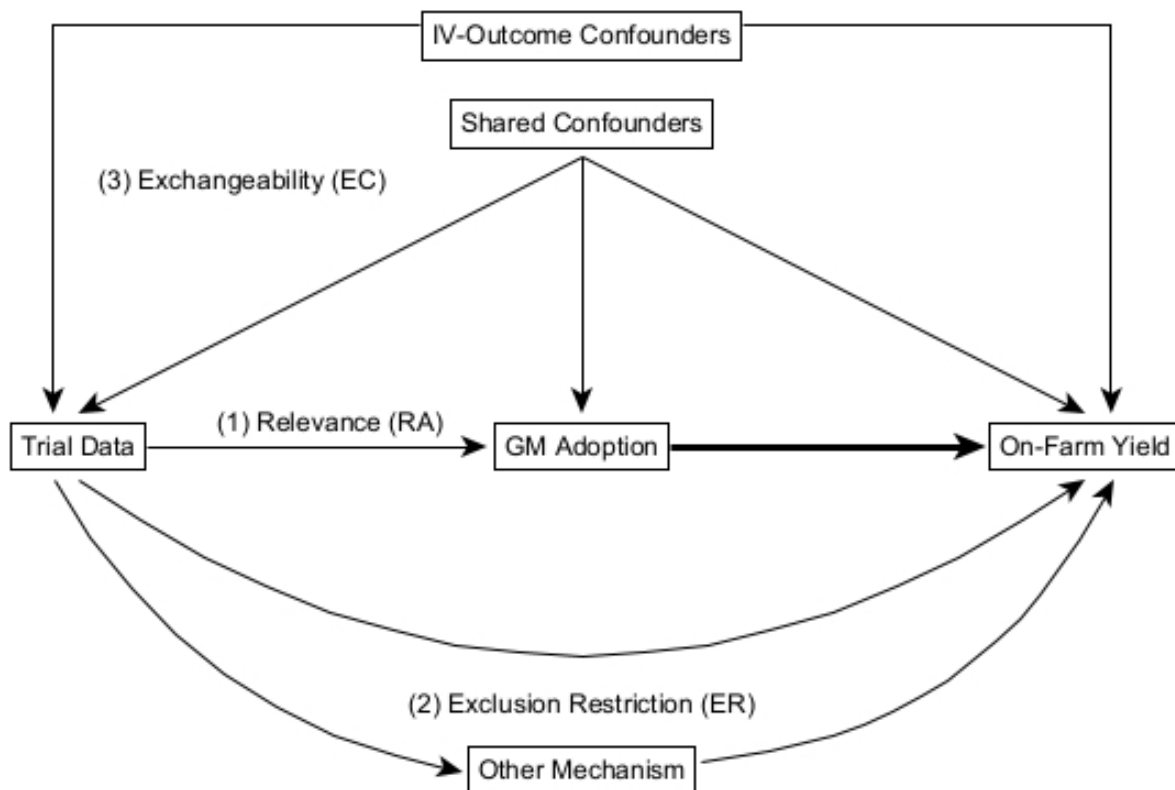
Producers rely on both their own experience and information from extension services to inform their production decisions, the latter of which is especially valuable for evaluating newly released technologies (Eklund 1983; Nalley et al. 2009; Genius et al. 2014; Krishnan and Patnam 2014; Maertens, Michelson and Nourani 2021; Lee and Moschini 2022; Abdulai 2023). Nearly 92% of extension services globally receive public funds and are administered through government, research institutions, and/or universities (Davis, Babu and Ragasa 2020). The goal of most public extension services is to deliver impartial, timely, and locally relevant information to producers through various channels including field days, web-based decision tools, and online and print publications. Producers may access this information directly themselves, or as is becoming increasingly common, through another party such as a seed sales representative or crop consultant. Importantly, the producer does not need to access the information directly for it to influence their decisions as extension information is widely circulated and shared among many actors in the agricultural community (Burlig and Stevens 2024).

Extension information is often generated through agricultural research activities such as field trials. In the United States (U.S.), much of the publicly funded agricultural research is conducted at land-grant universities and their branch experiment stations. There is at least one land-grant university in each state and over 600 experiment stations across the country (Pearson and Atucha 2015). Each year, these experiment stations conduct field trials to evaluate the performance of crop varieties in different environments, producing millions of data points annually. The trials are conducted under credible experimental protocols such as randomized complete block designs and best management practices that evolve across space and time. As a result, the trial data provides a reliable source of relative yield differences among varieties (Brennan 1984; Tack, Barkley and Nalley 2015). Of particular interest to this study, field trials

are a rich source of public information that may be repurposed by economists to study issues in agricultural production as (Heady 1957) demonstrated nearly 70 years ago.

We posit that variety trial data can be used to construct plausible instruments to identify the effect of endogenous technology adoption on farm productivity. In the proposed novel instrumental variable (IV) approach, instruments constructed from variety trial data are used to identify the effect of genetically modified (GM) corn on farm yield. Figure 1.1 provides a Directed Acyclic Graph (DAG) outlining our identification approach and the three conditions for instrument validity: (1) relevance (RA) or the instrument (trial data) is related to the exposure variable (GM adoption), (2) the exclusion restriction (ER) is satisfied or trial data only influences the outcome (on-farm yield) through adoption, and (3) exchangeability (EC) or the trial data does not share common causes with on-farm yield. Of the three, the RA condition can be empirically validated in a straightforward manner using so called “strong” instrument tests (Keane and Neal 2023) while the other two are much harder to establish in practice. For the ER there are two causal pathways, one directly to the outcome and the other through an intermediate mechanism. For EC there are also two types of violations, shared confounders that affect all three variables of interest and confounders that affect the trial data and on-farm yield. In practice, neither the ER nor EC conditions can be empirically validated using hypothesis testing.

Figure 1.1. DAG outlines the IV assumptions for credible identification and the relationships between variables in the empirical strategy.



Note: Valid instruments must satisfy three assumptions: relevance, exclusion restriction, and exchangeability. Trial data, GM adoption, and on-farm yield correspond to the instrument, exposure, and outcome variables, respectively. The bold arrow indicates the causal effect of interest. Figure was adapted from (Hui et al. 2024).

Figure 1.1 highlights the difficulty of obtaining valid instruments in farm settings due to the myriad of potential confounders both on- and off-farm. We overcome this challenge by processing the trial data in a clever way using two key steps. First, we lag the trial data by one year which has the advantage of both establishing the RA condition and blocking any pathway that depends on temporal variation (e.g., prices and growing conditions). Second, we difference the lagged trial data by subtracting conventional yields from GM yields thereby focusing exclusively on the GM yield differential, which will both make the instrument more relevant (i.e., “stronger”) and block spatial confounders (e.g., soil quality and climate). We provide more

details on this approach in the Empirical Strategy section below. Additionally, a recently developed data-driven approach, Some Invalid Some Valid IV Estimator (sisVIVE) (Kang et al. 2016), is employed to assess potential violations of the ER. To our knowledge, constructing instruments from extension information and the accompanying empirical strategy is novel to the literature and may be applied in many additional research contexts (i.e., technologies, crops, and/or locations).

The main findings from our analysis are threefold. First, the constructed instruments from field trial data are statistically strong and therefore provide a rich opportunity for future research to consider when estimating the effect of on-farm technology adoption. Second, failure to account for endogeneity does result in a substantial upward bias in the estimated productivity gains of approximately 24%. Third, after correcting for this bias the effect of GM corn adoption on productivity remains large at 19.6 bushels per acre (b/a), which provides another important datapoint in the literature showing the enhanced production efficiency of GM crops.

The remainder of the paper is organized as follows. The next section provides background information on GM crops and recent controversies in public policy arenas surrounding GM crops. The third section discusses the data, while the fourth describes our empirical strategy. The fifth reports our main results and several robustness checks and the final section provides concluding remarks.

1.2 Background

GM corn was commercialized in the U.S. in 1996 with the first varieties containing a trait for insect resistance (IR). Shortly thereafter, varieties containing traits for herbicide tolerance (HT) became available followed by stacked varieties containing both traits. Traits for IR are derived from *Bacillus thuringiensis* (*Bt*) and provide targeted pest control. HT crops express

tolerance to specific herbicides (e.g., glyphosate), allowing producers to control weeds without damaging the crop. GM corn has been widely adopted by producers covering 94% of all U.S. corn acres in 2024 (USDA ERS 2025).

The benefits associated with GM crop adoption have been well documented in the literature and include productivity gains (Qaim 2009; Fernandez-Cornejo et al. 2014; Klümper and Qaim 2014) as well as environmental and market-wide benefits (Smyth, Kerr and Phillips 2015; Brookes and Barfoot 2018; Ciliberto, Moschini and Perry 2019; Scheitrum, Schaefer and Nes 2020; Ala-Kokko et al. 2021; Hansen and Wingender 2023). Recent controversies have been renewed by policymakers expressing health concerns surrounding GM crops (Cirruzzo and Cancryn 2025) and new trade disputes and production bans have been initiated (Barrera 2025; Garrison 2023). The American Academy of Pediatrics urged parents to avoid foods with ingredients sourced from GM crops (Abrams et al. 2024) and Mexico cited this in their efforts to ban GM corn imports (Wadman 2024), despite the scientific consensus on the safety of GM technology (Institute of Medicine and National Research Council 2004; European Commission 2010; World Health Organization 2014; National Academies of Sciences Engineering and Medicine 2016). Others have suggested that GM adoption has failed to increase on-farm yield or decrease pesticide use (Gurian-Sherman 2009; Hakim 2016) and critics in the popular press often highlight a National Academies of Sciences Engineering and Medicine (2016) report which stated that there was little evidence that GM crops have increased yield potential.

GM technology adoption and its subsequent impacts remain a salient policy and empirical issue. The literature has acknowledged the empirical difficulty of estimating the causal effect of endogenous technology adoption. Previous studies have noted that without accounting for this parameter estimates obtained from directly estimating the GM effect on yield may be

biased (Shankar and Thirtle 2005; Shankar, Bennett and Morse 2008; Mutuc, Rejesus and Yorobe 2011; Kouser and Qaim 2014; Sanglestsawai, Rejesus and Yorobe 2014).

1.3 Data

Variety trial data, on-farm production data, and weather data are spatially merged at the location-year level. Each dataset is described in the following section which is accompanied by Table 1.1 that reports the descriptive statistics of select variables. The technique employed to spatially match the data is described in the *Empirical Strategy* section.

Table 1.1. Summary statistics of select variables.

Variable	Mean	SD	Min	Max
<i>Variety trial data (1992-2009)</i>				
Locations per year	79.61	34.03	7.00	115.00
Trial conventional yield	163.36	39.00	1.00	308.80
Trial single IR or HT yield	181.17	41.99	1.00	317.00
Trial stacked IR and HT yield	194.11	39.76	4.00	302.20
Trial multiple IR yield	194.10	34.30	1.00	283.20
Proximity to county (km)	87.19	95.92	1.20	674.32
<i>On-farm data (1980-2010)</i>				
Counties per year	665.71	9.07	637.00	675.00
County yield	118.96	33.86	4.55	207.46
GM adoption rate	0.20	0.28	0.00	0.96
<i>Weather data (1980-2010)</i>				
Degree days 0-10°C	1,549.13	95.23	1,209.68	1,780.27
Degree days 10-29°C	1,429.71	239.51	681.49	2,184.32
Degree days above 29°C	29.21	27.25	0.00	249.87
Precipitation (cm)	57.70	14.13	17.94	121.93
Precipitation squared (cm ²)	3,529.05	1,726.39	321.84	14,866.92

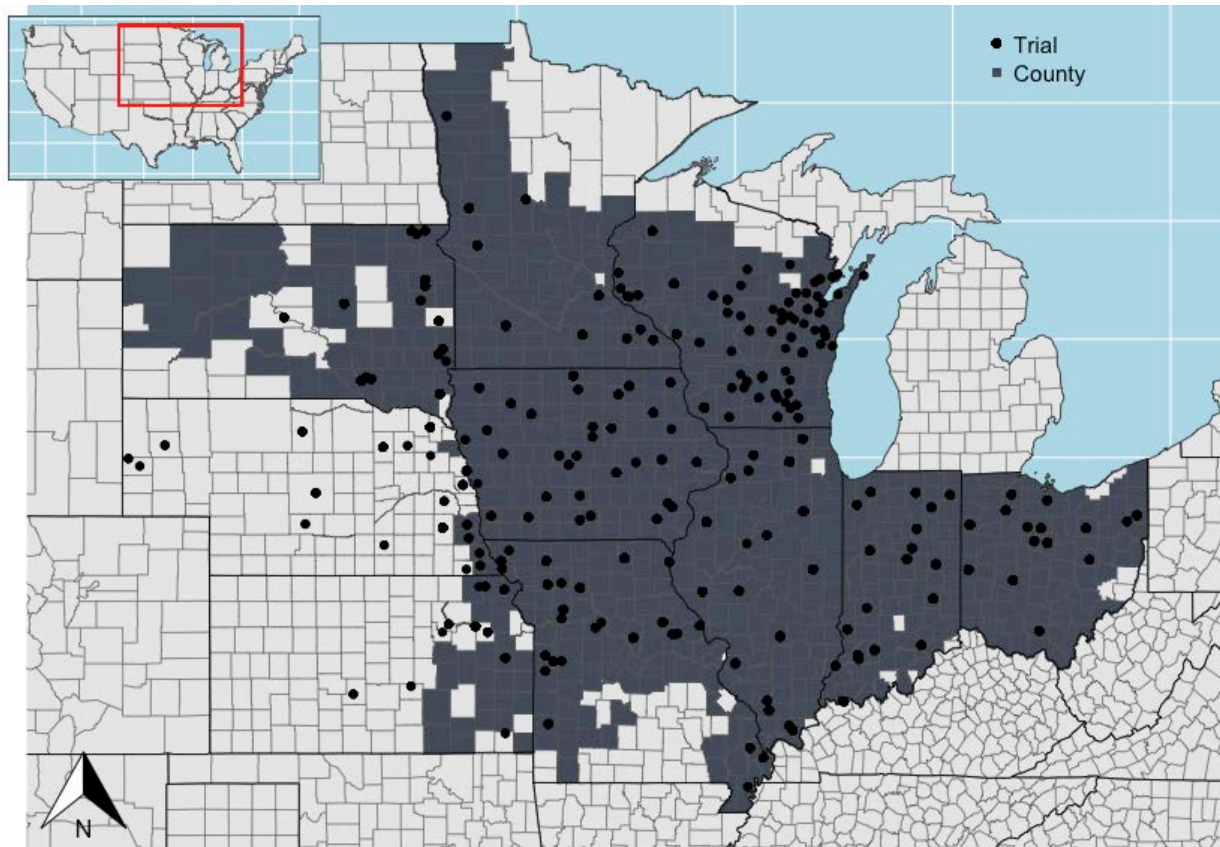
Notes: Variety trial data was obtained from annual field trial reports published by university agricultural extension services, on-farm yield and adoption data was obtained from USDA-NASS, and weather data was obtained from PRISM.

1.3.1 Variety Trial Data

Trial data was compiled by Nolan and Santos (2012) from university extension corn variety trial reports from the ten largest corn producing states in 1997-2009: Illinois, Indiana, Iowa, Kansas, Minnesota, Missouri, Nebraska, Ohio, South Dakota, and Wisconsin. The trial data spans 236 locations, 17 years, and includes over 20,000 varieties. In-sample locations are shown in Figure 1.2. On average, 80 locations conducted trials each year, however, the number of locations per year ranges from 7 to 115 (Table 1.1). The data are observed at the variety-

location-year level and includes information on yield and whether a variety is conventional or GM. Of the 20,507 varieties, 60% are conventional and 40% are GM. For each GM variety, the trait package is also noted and includes corn borer (CB) resistance; rootworm (RW) resistance; HT; CB and HT; RW and HT; CB and RW; and CB, RW, and HT.

Figure 1.2. Map of in-sample trial locations and counties: 1980-2010.



Note: Analysis focuses on dryland counties and not all trials get matched to a county each year.

To allow for different GM trait technologies to drive adoption, the trait packages were aggregated into one of three technology categories: single trait varieties, stacked trait varieties, and multiple trait varieties. Single trait varieties are characterized by one trait for either IR (CB or RW) or HT, stacked trait varieties have at least one IR trait and one HT trait (CB and HT; RW and HT; and CB, RW, and HT), and multiple trait varieties have multiple IR (CB and RW) traits. Table 1.1 provides yield statistics by these groupings.

In Appendix A, Figure A.1 in the shows the number conventional, single trait, stacked trait, and multiple trait varieties in the trial data over time. Notably, the first single trait varieties enter trials in 1992, stacked traits entered in 1995, and multiple traits entered in 2004. Prior to commercialization, there are a limited number of GM varieties present in trials as initial research and development efforts focused on a handful of varieties well adapted to specific local conditions (Falck-Zepeda, Traxler and Nelson 2000). We also observe the number of conventional varieties submitted into the trials decrease by 93.6% between 1990-2009, virtually reaching zero by 2009.

1.3.2 On-Farm Data

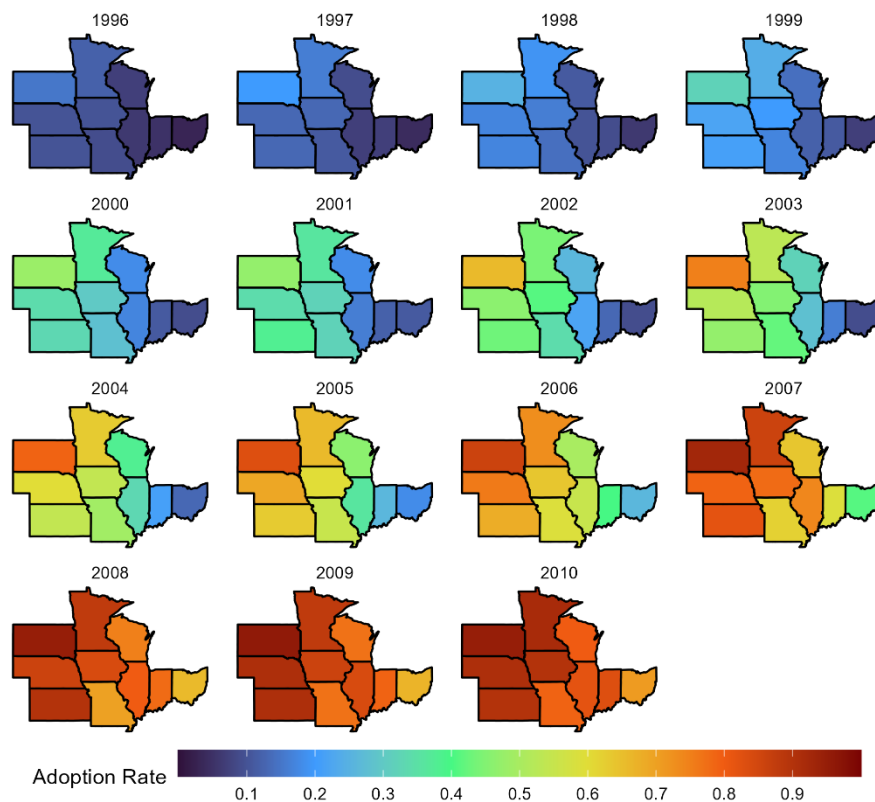
On-farm county-level corn production and harvested area data was obtained from the National Agricultural Statistical Service (NASS) Quick Stats database for the years 1980-2010 USDA NASS (2023) with yield being defined as their ratio. Following previous research (Lusk, Tack and Hendricks 2017; Xu et al. 2013) we used 1980 as the first year in the time series to allow for a roughly equal number of years pre- and post-GM with approximately 48% of observations in the former. Counties were omitted if more than 10% of harvested acres were irrigated or if yield was observed for less than two-thirds of the pre- or post-GM years. The resulting panel has 20,655 yield observations across 676 counties (Figure 1.2). Figure A.2 shows the considerable cross-sectional and temporal variation of on-farm yield and trial yield among the three trait technologies. Figure A.3 shows further evidence of this variation by state.

On-farm GM corn adoption rates were obtained from USDA Economic Research Service (ERS) from 2000-2010 (USDA ERS 2025). Due to limited data availability, the adoption rates used were reported at the state level, resulting in a spatially mismatched panel. This is alleviated by matching the state adoption rates to each in-sample county, although some heterogeneity may

be lost in this process. Importantly, the use of state-level aggregate adoption does not introduce bias in the GM effect estimate because the measurement error is uncorrelated with the observed state-level adoption (Lusk et al. 2017). Following Lusk et al. (2017), missing data from 1996-1999 were interpolated using predictions from a generalized linear model with a binomial family and a logit link function.

The state-level GM corn adoption rates from 1996-2010 are provided in Table A.1 and Figure 1.3 presents the spatial distribution of GM adoption over time. Interestingly, adoption rates tend to move southeast overtime in the states included in our sample, perhaps due to the earlier commercialization of varieties with CB resistance while RW resistance followed thereafter. The former (latter) is a more significant problem in the western (eastern) corn belt (National Research Council 2010).

Figure 1.3. Spatial distribution of in-sample on-farm GM corn adoption by state: 1996-2010.



Note: Adoption rates from 2000-2010 were obtained from USDA ERS and rates from 1996-1999 were interpolated. Interpolation procedure is described in further detail in the text.

1.3.3 Weather Data

Previous research linking GM adoption to yield has shown that weather is a potential confounder that could bias parameter estimates (Xu et al. 2013; Lusk et al. 2017). Precipitation and temperature data were obtained from PRISM Climate Group (2023) at the county-level following Schlenker and Roberts (2009). Daily minimum and maximum temperatures across the growing season (March-August) were interpolated using a sinusoidal approximation and used to construct degree day variables between 0-10°C, 10-29°C, and above 29°C. Figure A.4 depicts the cross-sectional and temporal variation of the weather variables.

1.4 Empirical Strategy

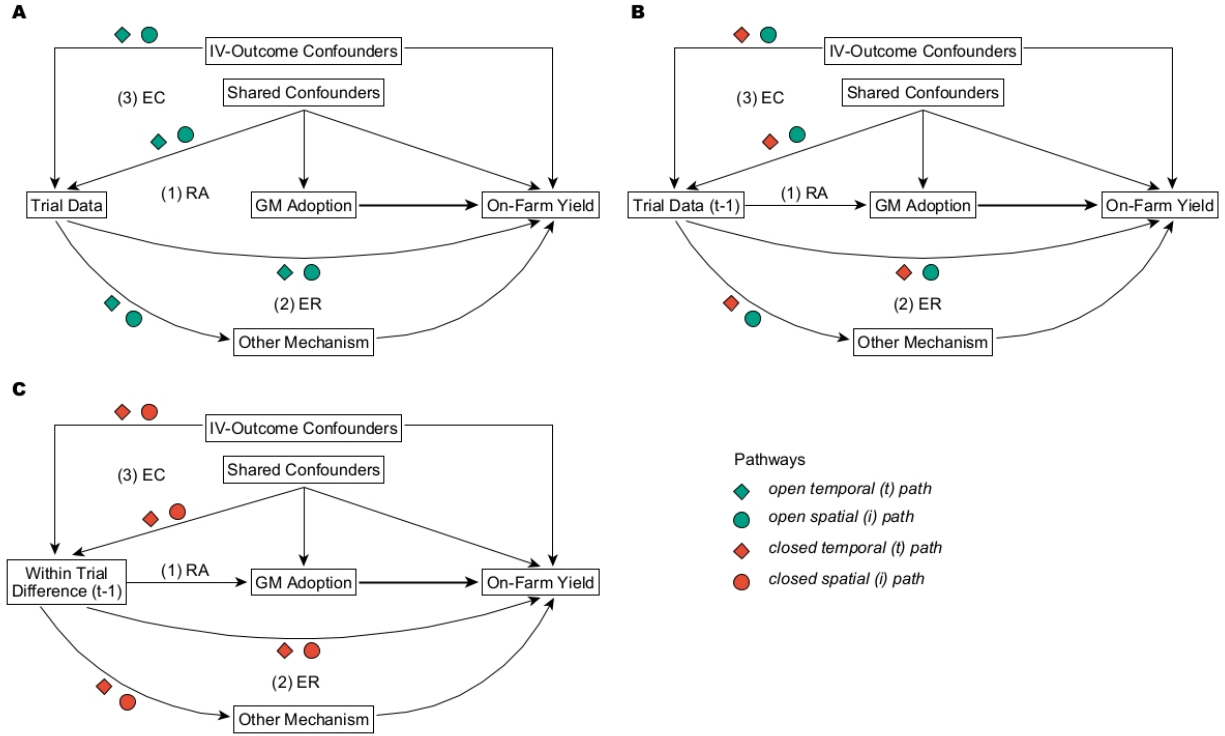
Our novel IV procedure leverages cross-sectional and temporal variation in information from extension variety trials to causally identify the effect of adoption on productivity. This procedure is detailed in the following section beginning with instrument construction followed by the two-stage least squares (2SLS) estimation.

1.4.1 Instrument Construction

Instruments are constructed to resemble information acquired by producers facing uncertainty regarding a novel technology. Either directly through extension services or indirectly through intermediaries (e.g., seed sales representatives, crop consultants, etc.) producers acquire data on the potential yield gains of a technology from annual variety trial reports. We remain agnostic through the exact channel producers receive this data as intermediaries often rely on publicly generated data (Wolf, Just and Zilberman 2001; Just, Wolf and Zilberman 2003).

Our identification strategy is provided in Figure 1.4 and highlights the benefits of our approach. Define the trial data as consisting of yields for both conventional and GM varieties, given by the set $\{y_{i,l,t}\}$ where y is the yield for variety i grown at trial location l in year t . Panel A corresponds to the use of these data and shows that (i) RA is not satisfied since the adoption decision is made before the trial data for that year is observed and (ii) there are a lot of open pathways in both the spatial (i) and temporal (t) dimensions. Examples of spatial confounders include soil, climate, and risk preferences; while examples of temporal confounders include prices, weather, pests, and disease.

Figure 1.4. DAGs outline the IV assumptions for credible identification and steps taken to construct valid instruments.



Panel B corresponds to the first step in our instrument construction, which is to lag the trial data by one year so that the relevant set becomes $\{y_{i,l,t-1}\}$. The first implication of this transformation is that the RA assumption is now satisfied as producers view trial reports from the previous year to inform their adoption decision in the current period. The second implication is that all the contemporaneous (i.e., temporal) pathways for both the ER and EC are now closed.

Panel C shows the second step in the instrument construction, where we focus on yield differences between the GM and conventional varieties within each year so that anything common among the varieties at that location in that year (e.g., growing conditions and/or management practices) gets netted out (Hutchins and Irwin 2025). More specifically, if i (j) indexes GM (conventional) yield in trial location l in year t then this signal is measured as

$$z_{l,t-1}^{\max} = \max_{i \in GM} \{y_{i,l,t-1}\} - \max_{j \in CO} \{y_{j,l,t-1}\}. \text{ One could also use the average of each group instead, but we}$$

consider the maximum to be a better signal as a single variety may result in yield gains that materialize on-farm. Averages are considered as a robustness check in the next section. One could also use last year's observed differential, $z_{l,t-1}^{max}$, or a cumulative average of the annual maximum differences over all historical years defined by $z_{l,t-1}^{cumax} = \frac{1}{N} \sum_{n=1}^N z_{l,t-n}^{max}$.¹ We focus on the latter in our preferred model but also consider single year measures as a robustness check.

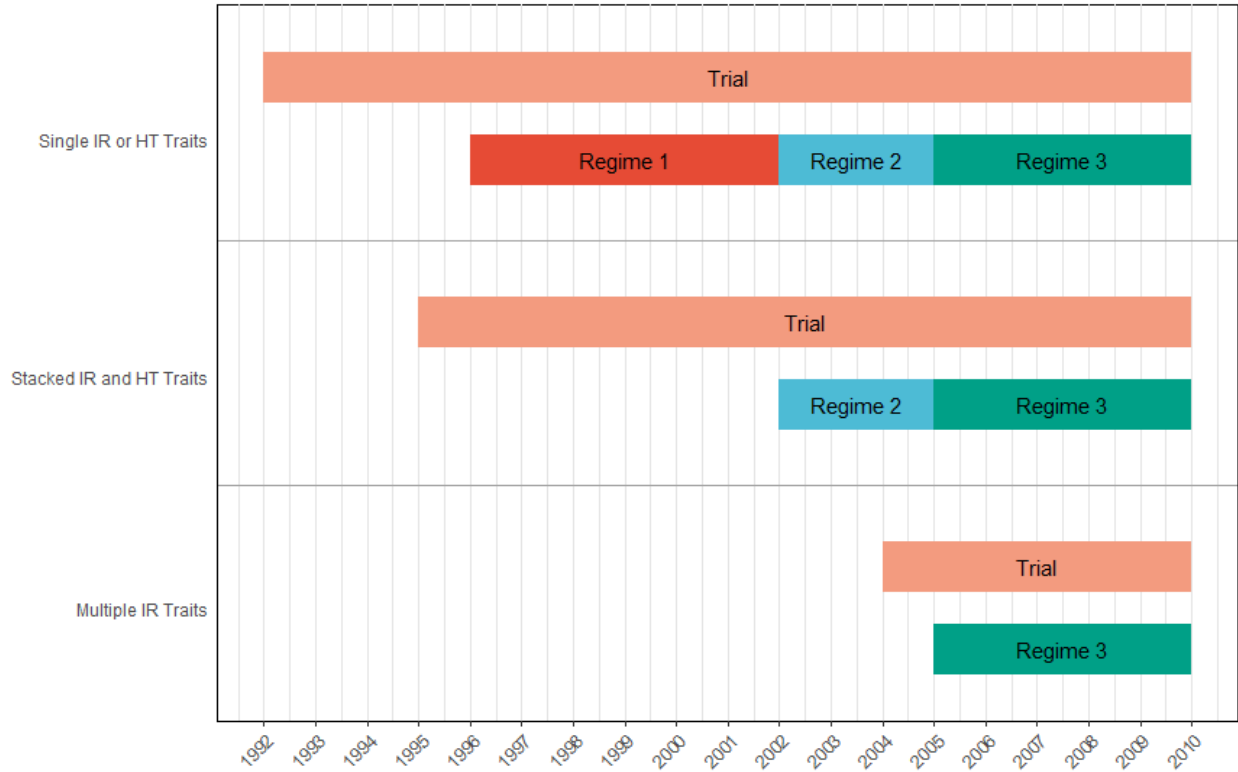
Here again we have two important implications of the described instrument construction, the first being that the resulting instrument is now more closely aligned with the GM adoption decision as producers considering switching will be more interested in relevant yields rather than the absolute yield level. The second implication is that all time-invariant (i.e., spatial) pathways for both the ER and EC assumptions are now closed.

So far, we have focused on the yield information constructed from the trial data or the *signal* producers use to inform their adoption decision. It is likely that producers will place some subjective measure of credibility on the signal, which we measure as the cumulative number of years that trial information is available. This assumes that as the variety trial signal accumulates over longer periods the more credibility the producer will attach to it. We refer to this as the *noise* around the signal and measure it as $z_{l,t-1}^{num} = \sum_{n=1}^N I_{l,t-n}$ where $I_{l,t}$ is an indicator variable that is equal to one if a GM variety appears in trial location l during year t . As with the signal, we use the lagged value $z_{l,t-1}^{num}$.

¹ This is similar to the distinction between naïve and weighted-average prices in the agricultural supply literature (Nerlove 1979). In practice it is impossible to know if producers aggregate the information over time, and if so, what discount they assign to sequentially distant information.

Thus far we have focused on two different aspects of information, next we focus on more granular subcategories of information by leveraging trait package differences across GM varieties, defined as single trait (CB alone; RW alone; HT alone), stacked traits (CB and HT; RW and HT; CB, RW, and HT), and multiple traits (CB and RW). An alternative definition that moves CB, RW, and HT into the multiple trait category is considered as another robustness check. Using the same approach as above, we define the cumulative maximum yield differential for each of these by $single_z_{l,t-1}^{cmax}$, $stacked_z_{l,t-1}^{cmax}$, and $multiple_z_{l,t-1}^{cmax}$; and the number of trials for each of these by $single_z_{l,t-1}^{num}$, $stacked_z_{l,t-1}^{num}$, and $multiple_z_{l,t-1}^{num}$. An interesting aspect of these trait packages is that they were sequentially rolled out over time with single trait released in 1996, stacked in 2002, and multiple in 2005. Thus, there are three distinct regimes that capture a widening availability of trait packages as depicted in Figure 1.5. It is also interesting to note that in some cases (e.g., stacked traits), there is an extensive amount of trial information already available to producers when commercialization begins.

Figure 1.5. Temporal attributes of trait technology categories.



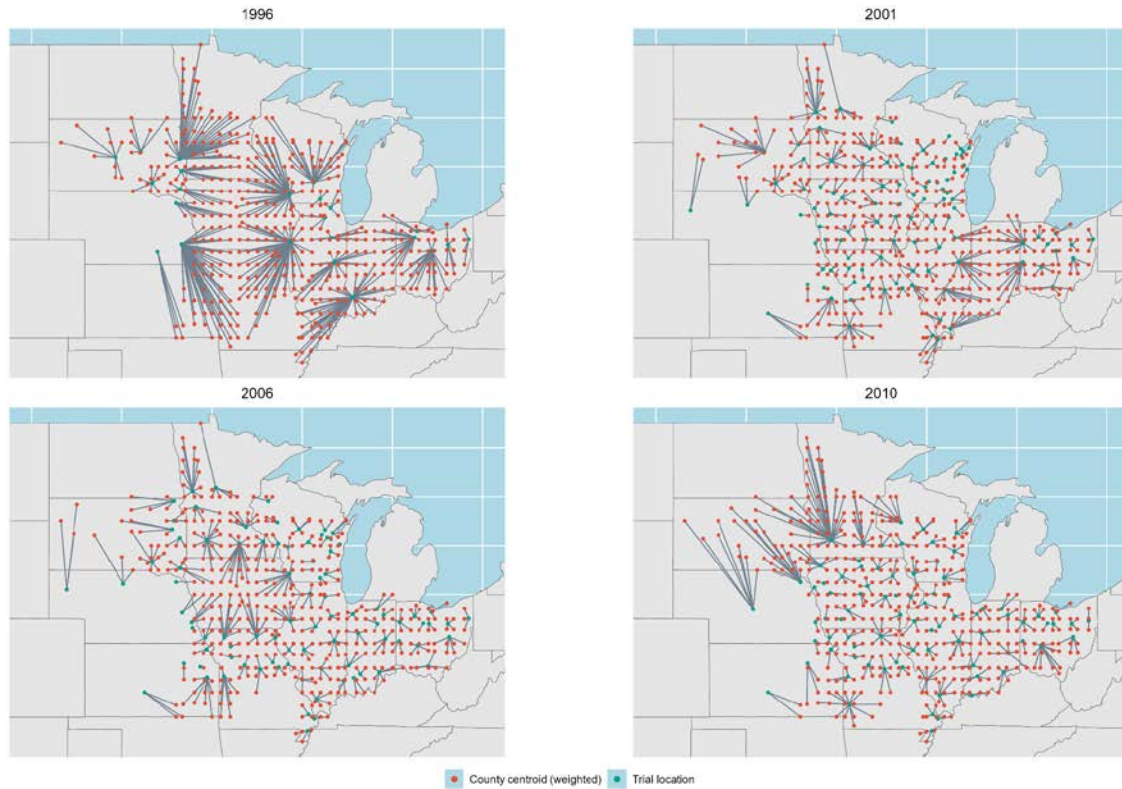
Note: Trial indicates the presence of a technology in at least one trial location. Regimes 1, 2, and 3 indicate the sequential roll out of each technology over time. Regime 1 spans 1996-2002 and starts when single traits are commercially available. Regime 2 spans 2002-2005 and starts when stacked traits are commercially available. Regime 3 spans 2005-2010 and starts when multiple traits are commercially available.

The final dimension of our information measures takes advantage of these commercial regimes to allow for switching behavior. This allows for the possibility that the availability of a new trait package changes the influence of the previous trait package, similar in spirit to the relaxation of the independent alternatives assumption in the revealed preferences literature (Train 2009). Define a regime-one indicator variable $R1$ as taking on a value of one if year $y \in [1996, 2002)$, regime-two $R2$ if $y \in [2002, 2005)$, and regime-three $R3$ if $y \geq 2005$. We expand the set of information measures by interacting these regimes with the yield differential (signal) and trial year (noise) variables.

Until this point, instruments are observed at the location l level in year $t-1$ while on-farm production data and weather data are observed at the county c level in year t . The instrument

dataset is merged with the county-level dataset by matching the county's crop-weighted centroid coordinates with the coordinates of the closest trial location in the instruments data (i.e., selecting the minimum linear distance in kilometers between a county centroid and trial location). Thus, the instruments are now specific to each county c in year t . Crop-weighted county centroid coordinates were obtained from Hsiang et al. (2013). The average trial proximity is 87.2 kilometers from a county with distances ranging from 1.2 to 674.3 kilometers (Table 1.1). We assume that proximity matches counties with trial locations that have similar agroclimatic conditions. Thus, producers can acquire information from a location that faces similar constraints and reasonably form an expectation regarding how a technology will perform on their farm. Importantly, previous work has found that farm proximity to a research station does not have an effect on farm productivity post 1950 (Kantor and Whalley 2019). Figure 1.6 shows the linear distances between each in-sample county and trial location by year for select years. We also observe that the number of in-sample trial locations generally increases over time as GM varieties enter more trials.

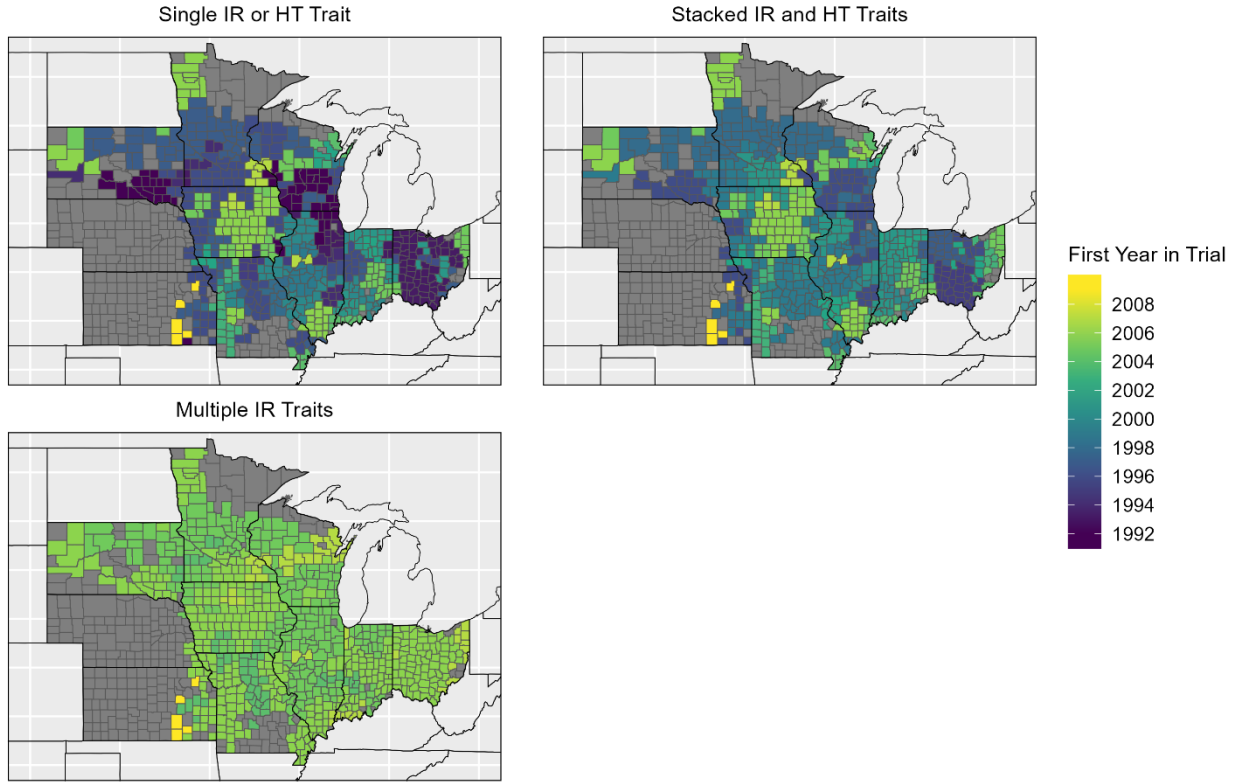
Figure 1.6. Matching in-sample county centroids with the closest in-sample trial location for select years: 1996, 2001, 2006 and 2010.



Note: The same matching procedure was conducted for each year in the data.

These information measures exhibit a substantial amount of cross-sectional and temporal variation. Figure 1.7 shows that novel varieties, while technically commercially released at the same time, do not enter all trial locations simultaneously. Thus, some producers have earlier access to information about new technologies that other producers may not have access to depending on whether they view these more distant trials as being locally informative. Additionally, the information signal itself exhibits substantial cross-sectional and temporal variation as depicted in the trait- and regime-specific cumulative maximum yield differential boxplots reported in Figure A.5.

Figure 1.7. Spatial distribution of the first year each technology enters a county's matched trial.



1.4.2 Model Estimation

We estimate the effect of GM adoption on corn yield using 2SLS. In the first stage, GM adoption is estimated using trial information alongside the exogenous regressors from the primary equation of interest, which follows Lusk et al. (2017) and Xu et al. (2013):

$$(1.1) \quad y_{c,t} = \alpha_c + \theta GM_{c,t} + \mathbf{x}_{c,t}' \boldsymbol{\beta} + \mu_{c,t}$$

where $y_{c,t}$ is corn yield in county c and year t measured in b/a; $GM_{c,t}$ is the covariate of interest measuring the fraction of acres planted with a GM variety; α_c is a county fixed effect; $\mathbf{x}_{c,t}$ is a vector of controls including a linear time trend, cumulative precipitation and its square, and low, medium, and high degree days; and $\mu_{c,t}$ is the error term. The trend variable controls for changes to technology and management practices that are not associated with GM adoption. County fixed

effects account for factors like soil type and climate. Standard errors are clustered by year to allow for a wide range of spatial correlation among the error terms.

The first stage regression includes the controls and fixed effects from the primary regression as well as the instruments from the variety trial information. In its simplest form this is given by

$$(1.2) \quad GM_{c,t} = \alpha_c + \mathbf{x}_{c,t}'\boldsymbol{\beta} + \gamma_1 z_{c,t-1}^{cmax} + \gamma_2 z_{c,t-1}^{num} + \varepsilon_{c,t}$$

where the z variables are the cumulative maximum yield differential ($z_{c,t-1}^{cmax}$) and number of trials ($z_{c,t-1}^{num}$) from the matched field trial locations. As discussed above, these variables are further extended to be specific bundles of technology, so the first stage becomes

$$(1.3) \quad GM_{c,t} = \alpha_c + \mathbf{x}_{c,t}'\boldsymbol{\beta} + \gamma_1 single_z_{c,t-1}^{cmax} + \gamma_2 stacked_z_{c,t-1}^{cmax} + \gamma_3 multiple_z_{c,t-1}^{cmax} \\ + \gamma_4 single_z_{c,t-1}^{num} + \gamma_5 stacked_z_{c,t-1}^{num} + \gamma_6 multiple_z_{c,t-1}^{num} + \varepsilon_{c,t}.$$

Lastly, we allow the parameters of the information variables to switch across commercial regimes so that the final (preferred) first stage regression becomes

$$(1.4) \quad GM_{c,t} = \alpha_c + \mathbf{x}_{c,t}'\boldsymbol{\beta} + R_1 \left[\gamma_1 \times single_z_{c,t-1}^{cmax} + \gamma_2 \times single_z_{c,t-1}^{num} \right] \\ + R_2 \left[\gamma_3 \times single_z_{c,t-1}^{cmax} + \gamma_4 \times stacked_z_{c,t-1}^{cmax} + \gamma_5 \times stacked_z_{c,t-1}^{num} \right] \\ + R_3 \left[\gamma_6 \times single_z_{c,t-1}^{cmax} + \gamma_7 \times stacked_z_{c,t-1}^{cmax} + \gamma_8 \times multiple_z_{c,t-1}^{cmax} + \gamma_9 \times multiple_z_{c,t-1}^{num} \right] + \varepsilon_{c,t}.$$

Note that we permit a full range of interactions for the cumulative maximum yield differentials but only the first regime-of-occurrence interactions for the number of trials, which reflects our assumption that the credibility of the signal is most important when new technologies first become available.

1.5 Results

In this section we first present the results from our preferred specification given by Equations (1.1) and (1.4) above. Since we cannot empirically validate either the ER or EC

conditions, we include county fixed effects, a time trend, and weather variables as additional covariates in both the first and second stages of the IV model as these have been shown to be important for identification in the literature (Xu et al. 2013; Lusk et al. 2017). Following our main results, we also conduct several robustness checks to investigate the role of overidentification and instrument validity and consider alternative specifications and instruments, potential confounding factors (e.g., pest pressure and seed price), and an alternative measurement of GM adoption.

1.5.1 Preferred Specification

The results from the first stage of the 2SLS model are reported in Table 1.2, and we see that seven of the nine candidate instruments are statistically different from zero at conventional significance levels. All six yield differentials instruments are positively associated with GM adoption, suggesting that higher in-trial yield gains are associated with higher on-farm adoption. Of the three years-in-trial instruments, only the one for multiple trait technologies was statistically significant on its own, however, a joint test for all three has a p-value less than 0.001. Taken together, this suggests that both the signal (GM yield gains) and the noise of that signal (number of trial years) are associated with on-farm adoption, which is consistent with previous research on seed variety selection (Barkley and Porter 1996; Nalley et al. 2009; Barkley 2024). Table 1.3 reports the results from the second stage alongside those from ordinary least squares (OLS), the former of which estimates a GM effect on yield of 19.6 b/a while the latter is much higher at 24.2 b/a. This represents a substantial upward bias of approximately 24%.

Table 1.2. First stage regression results of the preferred model for GM adoption.

	First stage of IV GM adoption rate
<i>Variables</i>	
Single cumulative max yield R1 (b/a)	0.002*** (0.001)
Single cumulative max yield R2 (b/a)	0.002*** (0.001)
Single cumulative max yield R3 (b/a)	0.004*** (0.001)
Stacked cumulative max yield R2 (b/a)	0.001*** (0.000)
Stacked cumulative max yield R3 (b/a)	0.002*** (0.000)
Multiple cumulative max yield R3 (b/a)	0.001** (0.000)
Single years in trial R1	-0.011 (0.008)
Stacked years in trial R2	0.015 (0.010)
Multiple years in trial R3	0.104*** (0.022)
Degree days 0-10°C	0.000 (0.000)
Degree days 10-29°C	0.000 (0.000)
Degree days above 29°C	0.000 (0.001)
Precipitation (cm)	0.002 (0.003)
Precipitation squared (cm ²)	0.000 (0.000)
Time trend	0.020*** (0.003)
County fixed effect	Yes
<i>Fit statistics</i>	
R2	0.85
RMSE	0.111
Wald (first stage)	49.848***
Observations	20,612

Notes: Standard errors are in parenthesis and are clustered by year. *, **, and *** denote statistically significance at the 10%, 5%, and 1% level, respectively. The first nine rows correspond to the instruments based on field trial information. R1, R2, and R3 represent the varying coefficients for each of the three regimes from 1996-2002, 2002-2005, and 2005-2010.

Table 1.3. GM effect on corn yield results from the second stage of the preferred model.

	OLS Yield (b/a)	Second stage of IV Yield (b/a)
<i>Variables</i>		
GM adoption rate	24.181*** (6.730)	19.564*** (6.641)
Degree days 0-10°C	0.050** (0.019)	0.051** (0.019)
Degree days 10-29°C	0.022 (0.014)	0.023 (0.015)
Degree days above 29°C	-0.678*** (0.074)	-0.675*** (0.075)
Precipitation (cm)	1.931*** (0.276)	1.931*** (0.288)
Precipitation squared (cm ²)	-0.018*** (0.002)	-0.017*** (0.003)
Time trend	1.044*** (0.187)	1.166*** (0.181)
County fixed effect	Yes	Yes
<i>Fit statistics</i>		
R ²	0.797	0.797
RMSE	15.23	15.246
Sargan		33.379***
Observations	20,612	20,612

Notes: Standard errors are in parenthesis and are clustered by year. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Given that nine instruments are used to estimate one endogenous variable, weak instrument detection and overidentification are of particular concern. The Kleibergen and Paap (2006) Wald test is conducted since standard errors are clustered, and results confirm that weak instruments are not a major concern (Table 1.2). However, a Sargan test was conducted, and the results suggest that instrument validity is indeed a concern (Table 1.3). Since each instrument is constructed to represent different types of variety trial information and likely explain different aspects of adoption, this result is not too alarming (i.e., if one instrument is invalid, it does not necessarily imply that all of the instruments are invalid) (Murray 2006). To investigate this

concern more fully, we conduct an extensive array of robustness checks including an alternative sisVIVE estimator that directly addresses this issue.

1.5.2 Data Driven IV Selection

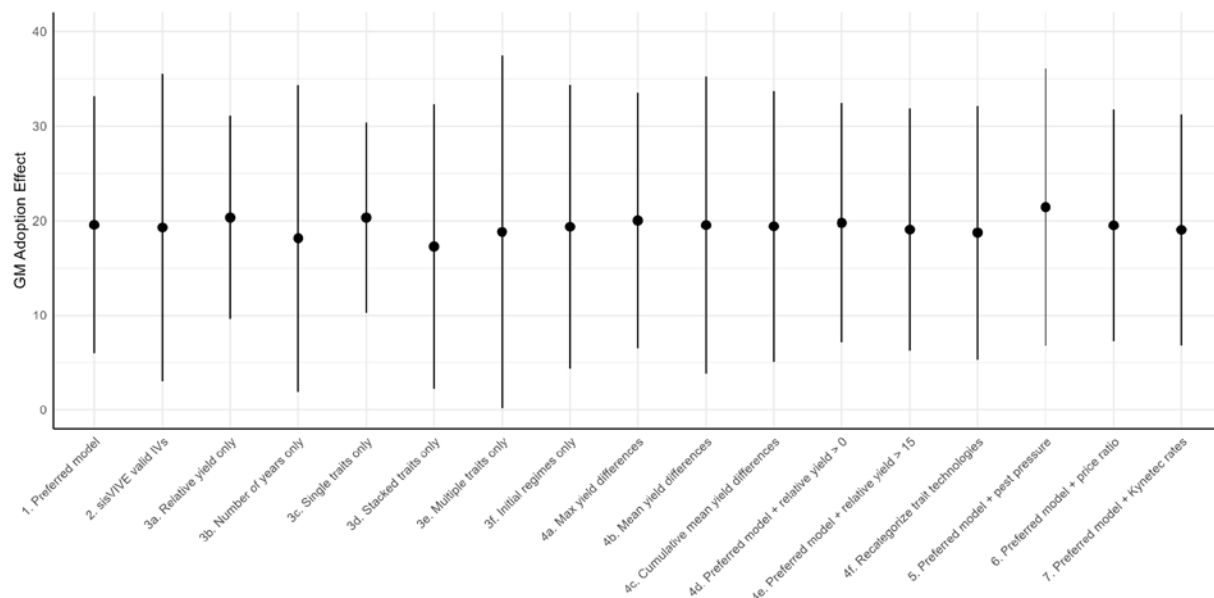
While we have economic justifications that support the validity of our instruments, the Sargan test indicates that some of the instruments lead to statistically different estimates on the impact of GM adoption compared to the others in the candidate instrument set. We also do not have *ex-ante* knowledge on which of the proposed instruments could violate the ER (i.e., we do not have complete knowledge about how producers use variety trial information to inform their on-farm decisions).

To address this concern, we utilize a recently developed data-driven approach developed by Kang et al. (2016), sisVIVE, which uses a penalized regression for the second stage equation while having all of the instruments added as additional regressors. If some instruments violate the ER, they will have non-zero coefficients in the second stage equation. Imposing a penalty allows this modified second stage equation to be estimated, which otherwise faces perfect collinearity. Similar to penalized regressions such as Lasso or elastic net, the challenge is to estimate the tuning parameter that governs the degree of penalization. sisVIVE performs a K-fold cross validation to select the optimal penalization parameter (λ). High values of λ impose a larger penalization and most of the instruments will be classified as valid while low values of λ will result in most of the instruments being classified as invalid.

The results obtained from the sisVIVE estimator confirm the Sargan test results that some of the nine instruments are invalid. Table A.2 reports the estimates of λ and the corresponding estimates of the GM effect, number of invalid IVs, and invalid IVs. After the 10-fold cross validation, the optimal λ chosen was 24.7. Given this penalization parameter, three GM yield

gain (signal) and one number of years (noise) instruments were deemed valid by the sisVIVE estimator (single cumulative max yield R3, stacked cumulative max yield R2, multiple cumulative max yield R3, and multiple years in trial R3). This reaffirms the result that producers use different types of information (i.e., the signal and noise) to assess technology bundles overtime to inform their adoption decision. Moreover, the sisVIVE estimator results in a similar GM effect obtained from the preferred model at 20.3 b/a as illustrated in Figure 1.8.

Figure 1.8. GM effect point estimates obtained from alternative specifications.



Note: Point estimates are reported at the 95% confidence interval with standard errors clustered by year. The (1) preferred specification and robustness checks including (2) data driven IV selection, (3) alternative subsets of instruments, (4) alternative measurement of instruments, (5) pest pressure covariates, (6) price ratio covariate, and (7) alternative GM adoption rates are all described in more detail in the text.

1.5.3 Alternative Subsets of Instruments

Overidentification was assessed further by specifying additional models that limit the number of instruments. We consider six alternative subsets of the nine instruments from the preferred model. The first two subsets considered separate the signal from the noise: (3a) the yield differential instruments only versus (3b) the number of years only. In both cases the associated GM estimate remains stable (Figure 1.8), implying that both types of information can provide credible identification. It is worth noting, however, that the standard error is much larger for the model that only includes the number of years instruments, which suggests that, given a choice, one should construct the signal instruments.

The next three subsets are based on instruments associated with the three distinct trait packages: (3c) single trait (four instruments), (3d) stacked trait (three instruments), and (3e) multiple trait (two instruments). We again find similar estimates compared to the preferred

model (Figure 1.8) suggesting that the evolution of GM technology does not need to be fully articulated in order to achieve credible identification. It is also worth noting that the standard error is much larger for the multiple trait model, suggesting some efficiency concerns associated with using later versions of the technology.

The final subset considers more direct linkages between the technology and its initial regime, considering only the first regime-of-occurrence interactions for both the signal and the noise (3f): single trait in R1 (two instruments), stacked trait in R2 (two instruments), and multiple trait in R3 (two instruments). As with the other subsets above, we find stable results compared to the preferred model (Figure 1.8). Taken together, the results from our preferred model are robust to several restrictions on the number of instruments used, providing evidence that variety trial data can provide credible identification using more parsimonious models than our nine-instrument approach.

1.5.4 Alternative Measurement of Instruments

Next, we focus on how the instruments are measured by maintaining the number of instruments at nine while altering their construction. First, we consider three alternative measurements: (4a) the max yield difference from the previous year, (4b) the mean yield difference from the previous year, and (4c) the cumulative mean yield difference from all previous years. These alternatives result in a similar GM effect ranging from 19.4-20.0 b/a (Figure 1.8), thereby suggesting that there are various credible ways that the yield signal can be measured from the variety trial data.

We also consider whether the size of the signal matters by restricting attention to yield differences that are (4d) greater than zero b/a and (4e) greater than 15 b/a. In practice these variables are constructed by zeroing out any value in the yield differential variables that is less

than zero or less than 15 b/a and then re-estimate the model. For these alternatives, the GM effect again remains stable (Figure 1.8), suggesting that it is not necessary to distinguish between the size of the yield premium signal when constructing instruments.

The final alternative we consider focuses on the trait category definitions by recategorizing (CB, RW, and HT) as a multiple trait variety (4f) given that two IR traits are present. Yet again the GM effect remains stable (Figure 1.8).

1.5.5 Pest Pressure

While focusing on lagged within-trial differences implicitly controls for many confounding factors that vary at the location-year level such as weather, soil, and management practices (Figure 1.4), it remains possible that pest pressure may be an unmeasured confounding variable which would violate the EC assumption. We consider this by re-estimating the model with three proxy weather variables for pest pressure: two preseason (December to March) freeze exposure variables (between -40 to -20°C and between -20 to -5°C) and cumulative precipitation in June. These variables were constructed using the same weather data in the primary specification from PRISM Climate Group (2023). Weather variables were considered as proxies since weather outcomes can influence many aspects of key stages of insect development. For example, sustained freeze exposure can increase egg mortality, reducing the pest population during the growing season (Chiang 1973; Godfrey et al. 1995; Ellsbury and Lee 2004; Toepfer and Kuhlmann 2005; Trnka et al. 2007; Jaksons, Falkner and Moltchanova 2022). Another sensitive stage for corn rootworm specifically is egg hatch which occurs around June in the Midwest. Egg mortality increases during this time if there is heavy rainfall (Trnka et al. 2007; Aglasan, Goodwin and Rejesus 2023).

When proxy variables for pest pressure were included in the estimation, the GM effect increases only slightly from 19.6 to 21.4 b/a (Figure 1.8) which suggests that accounting for pest pressure does significantly impact our results.

1.5.6 Seed Price

While it is unknown how exactly seed price is set, it has generally been observed that GM seed price increased substantially over the first decade of commercialization. This may be due in part to factors such as market concentration, intellectual property rights, and increased development costs (MacDonald, Dong and Fuglie 2023). Of interest to this study, is whether observed within-trial yield differences are considered when firms set their price, which could violate the ER assumption by linking our instruments to on-farm yield if the price effect does not solely operate through the adoption decision. We examine this possibility by incorporating a price ratio in the estimation constructed from price data for GM and non-GM corn seed collected from USDA NASS (2023). Since this data starts in 2002, missing ratios were interpolated back to 1996 using a linear trend regression. Including this ratio in the estimation results in a parameter estimate of 19.5 b/a (Figure 1.8) which suggests that it is not a major concern.

1.5.7 Alternative GM Adoption Rates

The final alternative model we consider focuses on the potential measurement error that the GM adoption interpolation approach may be introducing. As discussed in the Data section, the GM adoption rates were obtained from USDA ERS (2025) from 2000-2010, and missing data was interpolated from 1996-1999. For the last robustness check, the preferred specification is re-estimated using a different GM adoption dataset that does not rely on interpolation in the first three years. This adoption data was obtained from Lee, Ji and Moschini (2022) and is constructed by Kynetec USA using farm-level observations of seed choices by U.S. producers.

Notably, Kynetec's data begins in 1996. Re-estimating the preferred model using this data results in a GM effect of 19.0 b/a (Figure 1.8). Thus, we conclude that interpolating GM adoption rates for the years 1996-1999 has a negligible effect on the parameter estimates.

1.6 Conclusions

Since adoption is an on-farm decision variable, it is empirically challenging to identify its effect on farm outcomes such as yield productivity due to endogeneity concerns. In this paper, we proposed a novel empirical approach that uses instruments constructed from extension information (i.e., variety trial data) to identify the effect of a new technology on farm yield. Our results indicate that failure to account for the endogeneity of the adoption decision results in a substantial upward bias in the estimated productivity gains. After correcting for this bias through our IV approach, the GM effect on yield remains large at 19.6 b/a. Although previous estimates in the literature may be biased upward, our results are inconsistent with the claim that GM corn does not increase productivity (Gurian-Sherman 2009; Hakim 2016; National Academies of Sciences Engineering and Medicine 2016). Instead, we conclude that the GM effect is quantitatively different but not qualitatively different. Moreover, this point estimate was robust to several alternative specifications including restrictions on the number of instruments used. This suggests that variety trial data can provide credibly identified results under more parsimonious models than our preferred approach.

Quantifying realized yield gains from technology adoption remains an important issue in the agricultural economics literature. To our knowledge, this article is the first to use variety trial data to causally identify the effect of on-farm technology adoption on production outputs. Variety trial data has been used by agricultural economists to study yield performance (Qaim 2003; Nolan and Santos 2012; Chavas, Shi and Lauer 2014; Nalley et al. 2016; Shew et al.

2021), management practices (Mulimbi et al. 2023), and to conduct climate change analysis (Lobell et al. 2011; Tack, Barkley and Nalley 2014; Tack et al. 2016). These previous studies help researchers understand the drivers of adoption (i.e., improved yield, disease resistance, etc.) but do not causally explain the on-farm effects of adoption. Our study demonstrates that variety trial data can bridge this gap in the methodology and is general enough to be applied in additional contexts (i.e., technologies, crops, and/or locations).

Perhaps the greatest limitation of this approach stems from the current data management challenges associated with developing large scale field trial datasets. Generally, field trials are conducted under a larger institutional umbrella; however, the experiment stations where they are conducted tend to be decentralized. This is generally seen as a positive since experiment stations may conduct trials relevant to their local stakeholders, but this decentralization makes data management challenging. Each land-grant university (or CGIAR experiment station) has their own procedure for collecting, storing, and publishing data (Hyman et al. 2017; Leonelli et al. 2017). This results in a substantial amount of variability between data products (or reports) with respect to data quality, quantity, and format. Due to the heterogeneous nature of this data, a large amount of time and labor is often required to assemble and clean the data with this process becoming more complex as the scope of the analysis increases to include more states or countries (Brown et al. 2020).

Open data and data sharing initiatives have increased interest in combining and reusing datasets in many academic fields including those under the agricultural umbrella (Hyman et al. 2017; Leonelli et al. 2017; Finger et al. 2024). Notably, this study was possible, in part, due to other researchers sharing an existing dataset that they assembled and used in previous work (Nolan and Santos 2012). In some corners of the academic literature, there has been increased

recognition that field trial data can be applied to different research contexts (Reynolds et al. 2017; Reynolds et al. 2012). Importantly, field trials are not only conducted for the sake of evaluating variety performance, but also trials are conducted to examine specific management practices (e.g., irrigation, seeding rates, fertilizer use, pesticide use, etc.). There may be opportunities to learn from other fields that have developed public databases of experimental data such as genomics, phenomics, and bioinformatics (Tardieu et al. 2017; Bolger et al. 2019; Esposito et al. 2019; McFarland et al. 2020) to enable researchers to take advantage of the large amounts of data produced from expensive field trials.

Chapter 2 - Effects of Warming on Cool-Season Pulse Varieties in

North America

2.1 Introduction

Climate change is expected to have detrimental impacts on agriculture and has already affected crop productivity globally (Ray et al. 2019; Ortiz-Bobea et al. 2021). More severe and frequent extreme weather events increase production variability and decrease productivity, threatening food security and rural livelihoods (Rosenzweig and Parry 1994; Lobell et al. 2008; Vermeulen, Campbell and Ingram 2012). The impacts of climate change are spatially heterogeneous and are expected to affect regions at lower latitudes more severely than those at higher latitudes. Similar to other temperate regions, projected climatic changes in the Northern Plains of the United States and western Canada include warmer temperatures, more frost-free days, and increased precipitation (Wienhold et al. 2018; Mapfumo et al. 2023). Some argue that warmer temperatures may benefit temperate regions through gains in productivity (Costinot, Donaldson and Smith 2014; Lesk, Rowhani and Ramankutty 2016; Jägermeyr et al. 2021; Helman and Bonfil 2022) or through the expansion of suitable land areas for production (Zabel, Putzenlechner and Mauser 2014; Yue, Zhang and Shang 2019; Manners, Varela-Ortega and Van Etten 2020; Heikonen et al. 2025). Others have found that the net effect of warmer temperatures on yield is negative despite reductions in cold damage providing some benefits to yields (Tolhurst and Ker 2025). Nevertheless, the impact of climate change on agriculture at high latitudes remains a topic of debate.

Cool-season pulse crops have been characterized as resilient to weather extremes, such as heat, drought, excess water, and freeze exposure, under present-day climatic conditions (Cutforth et al. 2007). The impacts of future weather extremes on pulse crops such as field pea and lentil

are unknown as previous studies have focused on cereal grains and oilseed crops (e.g., barley, canola, corn, oats, soybean, and wheat) (Arthur and Abizadeh 1988; Kutcher, Warland and Brandt 2010; An and Carew 2015; Carew et al. 2018; Kukal and Irmak 2018; Morgounov et al. 2018; Qian et al. 2018; Qian et al. 2019). In this study, we examine the impacts of abiotic stress on field pea and lentil yields in the high latitudes of North America. We focus a region that includes parts of the Northern Plains of the United States (Montana, North Dakota, Washington, and Idaho) and western Canada (Saskatchewan and Manitoba). In recent decades, this area has become a major production region for pulse crops, producing 30% of the world's field pea and 38% of the world's lentil supply (FAO 2023). Field pea and lentil are consumed by low-income and high-income countries alike, serving as important sources of protein and nutrients in low- and middle-income countries (Joshi and Rao 2016; Joshi, Timilsena and Adhikari 2017; Khazaei et al. 2019) and used as ingredients in enriched protein foods and plant-based proteins in high-income countries (Clément et al. 2018; Warne et al. 2019; Troya et al. 2022; Panescu et al. 2023). Aside from their relevance to food security, pulses increase crop diversity in the region which is considered to be a climate change adaptation strategy (Degani et al. 2019; Hufford, Berny Mier y Teran and Gepts 2019; Bowles et al. 2020; Tamburini et al. 2020).

Our approach combines variety-specific field pea and lentil yield observations with weather data to estimate yields as a function of observed weather. Then, we project yield outcomes under future climate scenarios. The yield observations were collected from a novel field trial dataset constructed from variety trial reports conducted in four U.S. states (Idaho, Montana, North Dakota, and Washington) and two Canadian provinces (Manitoba and Saskatchewan). This dataset includes over 18,000 observations from 796 field pea and 220 lentil varieties grown across 87 locations in the U.S. and Canada from 2001 to 2023. Additionally,

models are extended to estimate the impacts of weather and future warming on two quality measures (test weight and protein content). We identify temperature thresholds of 29°C and 30°C for field pea and lentil, respectively, beyond which each additional degree day of extreme heat reduces field pea yield by 1.0% and lentil yield by 2.6%. Even after accounting for less freeze damage, the net effect of warming on field pea and lentil yields is negative (-6.8% to -18.9%). Additional results find that the net effect of warming on field pea protein content is moderately positive (+2.5% to +5.6%) while the effect on field pea and lentil test weight is small and negative (-0.9% to -0.1%).

2.2 Methods

2.2.1 Data

Since on-farm production data for field pea and lentil at the variety level was limited, a novel dataset was created from publicly available field trial reports from the largest producing field pea and lentil provinces in Canada (Manitoba and Saskatchewan) and states in the U.S. (Idaho, Montana, North Dakota, and Washington)². In Canada, these trials were conducted through producer associations while trials in the U.S. were conducted through university experiment stations. In both cases, these trials were conducted using randomized control block design with the explicit goal of providing producers with independent and unbiased information on variety performance. Data was collected for field pea and lentil yield at the variety-location-year level. Quality measures including test weight and protein content were collected at the variety-location-year level when available (this information was not collected at every trial). Additional information on agronomic practices including planting date, harvest date, and

² With the exception of Alberta because actual yield by location was not publicly available. Alberta Pulse Growers variety trial reports only included percent yield relative to a check variety and were aggregated by soil zone.

irrigation were collected at the location-year level. Irrigated field trials were not included in-sample. We only included locations that appeared in the data for at least two years and cultivars that appeared for at least two trial years in-sample. This extensive data included 18,407 observations, spanned 87 locations, 23 years, and included 376 field pea and 139 lentil varieties.

The field trial data was combined with location specific weather data. Gridded daily maximum temperatures, minimum temperatures, and precipitation during the growing season for each location were obtained from Daymet at the 1x1 kilometer level (Thornton et al. 2022). The growing season was defined at the crop-location-year level and started on the day of planting and continued through the day of harvest. Planting and harvest dates were typically noted in the field trial reports. For location-years missing these dates, planting date predicted values were obtained by regressing the planting date on the longitude and latitude with year fixed effects (or a year trend). Similarly, harvest date predicted values were obtained by regressing the harvest date on longitude, latitude, and planting date with year fixed effects (or a year trend). Following Schlenker and Roberts (2009), a sinusoidal distribution was fit between the daily minimum and maximum temperatures to estimate exposure for each degree Celsius. These exposure variables, along with daily precipitation, were subsequently summed across the growing season.

2.2.2 Regression Models

For field pea and lentil, the following model was estimated to obtain variety-specific weather effects on yield

$$(2.1) \quad y_{ijt} = \alpha_i + \alpha_j + \alpha_1 t + f(\mathbf{w}_{ijt}; \boldsymbol{\beta}) + \varepsilon_{ijt}$$

where y_{ijt} was log yield for variety i at location j in year t . α_i and α_j were the variety and location fixed effects, respectively. t was a linear trend, $f(\mathbf{w}_{ijt}; \boldsymbol{\beta})$ captured the potential

nonlinear effects of weather $\mathbf{w}_{ijt}$ on output, and ε_{ijt} was the error term capturing unobservable output determinants. Variety fixed effects, α_i , controlled for genetic changes induced by breeding efforts. Time-invariant and spatially-variant factors like soil type were controlled for using location fixed effects, α_j . The trend variable t controlled for any changes in best management practices over time. The standard errors were clustered by year because the error terms ε_{ijt} were likely heteroskedastic and spatially correlated.

The potentially nonlinear effects of weather on yield were obtained through estimating the following equation

$$(2.2) \quad f(\mathbf{w}_{ijt}; \boldsymbol{\beta}) = \beta_1 DDLow_{ijt} + \beta_2 DDMedium_{ijt} + \beta_3 DDHigh_{ijt} + \beta_4 F_{ijt} + \beta_5 P_{ijt} + \beta_6 P_{ijt}^2$$

where $DDLow_{ijt}$ were the degree days between 0°C and the lower threshold, $DDMedium_{ijt}$ were the degree days between the lower and upper threshold, and $DDHigh_{ijt}$ were the degree days above the upper threshold. Together, these variables provided a piecewise linear effect of temperature on yields. F_{ijt} was exposure in days to freezing temperatures and captured the potential benefits of warmer temperatures on yield, and P_{ijt} was cumulative precipitation.

The predicted yield impacts under +1 and +2°C warming used the average weather at each location from 1994 to 2023 to calculate the change in yield relative to the baseline climate. The projected impacts were calculated as follows

$$(2.3) \quad impact_k = 100 \left[e^{(\mathbf{w}_k - \mathbf{w}_0)\boldsymbol{\beta}} - 1 \right]$$

where k specified the warming scenario, $\mathbf{w}_k$ was the weather for the warming scenario k , $\mathbf{w}_0$ was the baseline average weather, and $\boldsymbol{\beta}$ were the estimates obtained after estimating Equations

(2.1) and (2.2). $\mathbf{w}_k$ for each warming scenario were calculated by increasing the baseline weather by +1 and +2°C and recalculating the weather variables.

Additional models (average temperature, average minimum and maximum temperatures, and step function) along with the preferred piecewise linear model were compared against a baseline model with no temperature information. The baseline model was specified as

$$(2.4) \quad f(\mathbf{w}_{ijt}; \boldsymbol{\beta}) = \beta_1 P_{ijt} + \beta_2 P_{ijt}^2.$$

Next, the average temperature model was specified as

$$(2.5) \quad f(\mathbf{w}_{ijt}; \boldsymbol{\beta}) = \beta_1 P_{ijt} + \beta_2 P_{ijt}^2 + \beta_3 \text{Avg}T_{ijt} + \beta_4 \text{Avg}T_{ijt}^2$$

where $\text{Avg}T_{ijt}$ was the average daily temperature. The average minimum and maximum temperature model was specified as

$$(2.6) \quad f(\mathbf{w}_{ijt}; \boldsymbol{\beta}) = \beta_1 P_{ijt} + \beta_2 P_{ijt}^2 + \beta_3 \text{Min}T_{ijt} + \beta_4 \text{Min}T_{ijt}^2 + \beta_5 \text{Max}T_{ijt} + \beta_6 \text{Max}T_{ijt}^2$$

where $\text{Min}T_{ijt}$ and $\text{Max}T_{ijt}$ were the daily minimum and maximum temperatures, respectively.

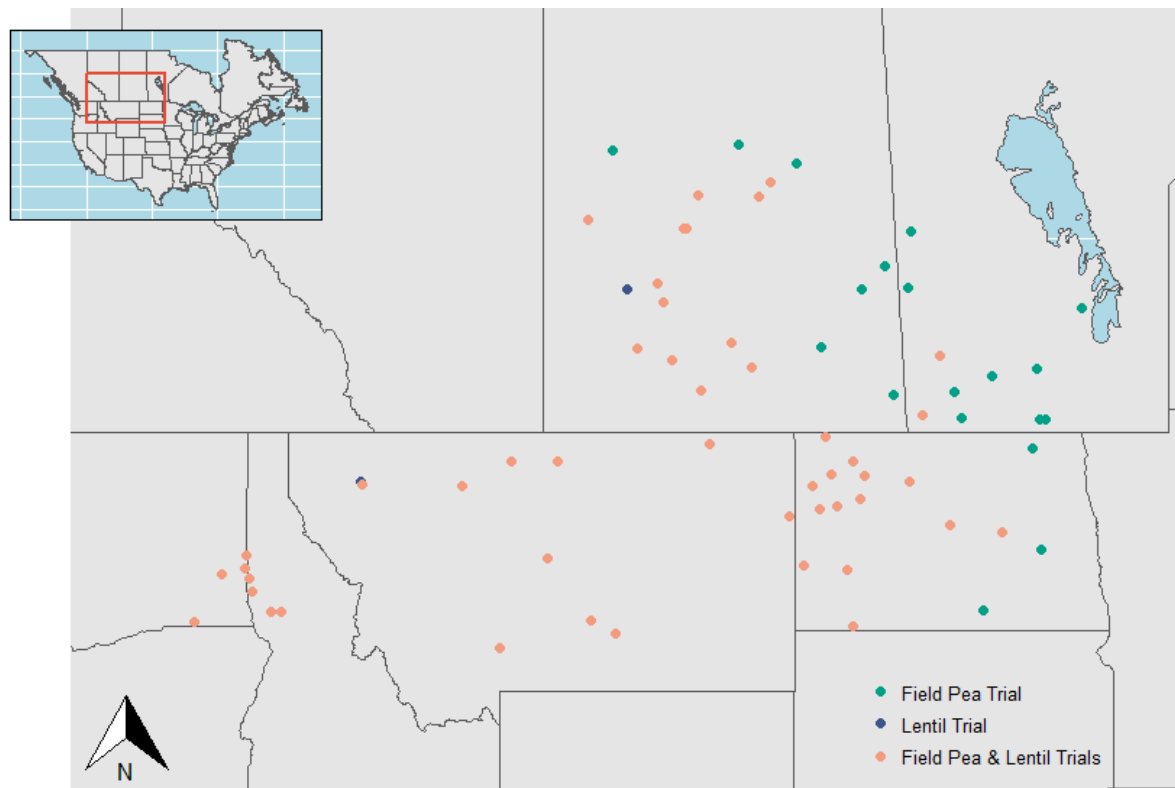
To investigate the effects of weather on quality, the dependent variable in Equation (2.1) was replaced with log test weight and log protein. The effects on test weight were estimated for both field pea and lentil. Prior to estimation, a filter is applied to remove extreme outliers in the data. We only included field pea test weights less than 50 bu/lb and lentil test weights between 30 and 90 bu/lb. The effects on protein content were estimated for field pea only due to limited observations of lentil protein content in the data.

2.3 Results

Figure 2.1 shows the locations of the dryland field pea and lentil trials across the Northern Plains of the U.S. and western Canada. 68.5% of the trial locations in the data conduct both field pea and lentil trials with the remaining 26.0% and 5.5% conducting only field pea and

lentil trials, respectively. Field pea trials were conducted at 69 locations while lentil trials occurred at 54 locations between the years 2001-2023. We only included varieties that appeared in at least two trial years. There were 376 unique field pea varieties, and 139 lentil varieties present in the data. In Appendix B, Tables B.1 and B.2 provide in-sample location characteristics (e.g., number of years, first year, last year, number of cultivars, and number of observations) for field pea and lentil trials, respectively. Varieties were entered into trials by both public and private breeding programs. On average, a field pea variety was observed in a trial for 5.2 years and a lentil variety for 8.0 years. The number of years any variety was in a trial was wide ranging and spanned the number of years in the data from two to 23 years as shown in panel A of Figures B.1 and B.2. Panel B reflects that newer varieties have fewer trial years in the data and that newer varieties entered the trials up until the last year of the time series in 2023. On average, a field pea variety appeared in 6.6 trial locations per year while a lentil variety appeared in 6.2 trial locations per year. Substantial in-trial yield variation was observed for both field peas and lentils as shown in Figure B.3.

Figure 2.1. Map of in-sample field pea and lentil trial locations: 2001-2023.



Notes: Data was collected from annual variety trial reports from Canada (Manitoba and Saskatchewan) and the U.S. (Idaho, Montana, North Dakota, and Washington). Variety trial reports were published by producer associations in Canada and university extension services in the U.S.

The trial data was matched with daily weather information throughout the growing season for each location-year. Tables B.3 and B.4 report the yield (MT), growing season dates (e.g., seeding and harvest day of the year), and weather variables (e.g., daily minimum and maximum temperature, cumulative precipitation, and freeze exposure) by location for field pea and lentil, respectively. The growing season was specific to each location-year and was defined from seeding to harvest day. The average growing season for field peas was May 5 through August 20 and May 2 through August 25 for lentils. Characteristic of the Northern Plains of the U.S. and prairie provinces of Canada, Figures B.4 and B.5 show the considerable amount of variation observed in the weather data.

2.3.1 Temperature Thresholds

Following the procedure outlined in Schlenker and Roberts (2009), degree days were calculated using a sinusoidal interpolation of temperature exposure within each day. To capture the nonlinear effects of extreme heat exposure on field pea and lentil production, a piecewise linear model was specified and estimated using the degree day variables. The piecewise linear model incorporated three measures of temperature exposure: degree days between 0°C and the lower threshold, degree days between the lower and upper thresholds, and degree days above the upper threshold. For field pea and lentil, the minimum bound was set to 0°C, the minimum temperature for germination (Roberts et al. 1988; Ney and Turc 1993). Temperature thresholds were selected by minimizing the mean squared errors of the crop-specific regressions (Equation 2.1).

For field peas, the lower threshold was identified as 12°C and the upper threshold as 29°C as reported in Table B.5. For lentils, the lower threshold was 6°C and upper threshold was 30°C as reported in Table B.6. These thresholds were consistent with values reported in the literature from experimental settings (Kumar et al. 2021; Devi et al. 2023; Bhandari et al. 2020; Sita et al. 2017). Thus, extreme heat is crop-specific and occurs when temperatures are above 29°C for field peas and above 30°C for lentils. These extreme heat thresholds are greater than those identified for barley (27°C), canola (25°C), and oats (27°C) and are similar to those identified for corn, flax, spring rye, soybean, and spring wheat (29-30°C) (Schlenker and Roberts 2009; Robertson et al. 2013; Tolhurst and Ker 2025). This suggests that field pea and lentil may be relatively more heat resilient (or exhibit similar levels of susceptibility to heat stress) than other crops commonly grown in this region. Nevertheless, the extreme heat thresholds are less than those identified for crops more common to lower latitudes such as cotton, rice, sorghum,

and hard red winter wheat (32-34°C) (Schlenker and Roberts 2009; Tack et al. 2015; Bheemanahalli et al. 2016; Tack et al. 2016; Tack, Lingenfelser and Jagadish 2017; Miller, Tack and Bergtold 2021).

2.3.2 Nonlinear Temperature Effects

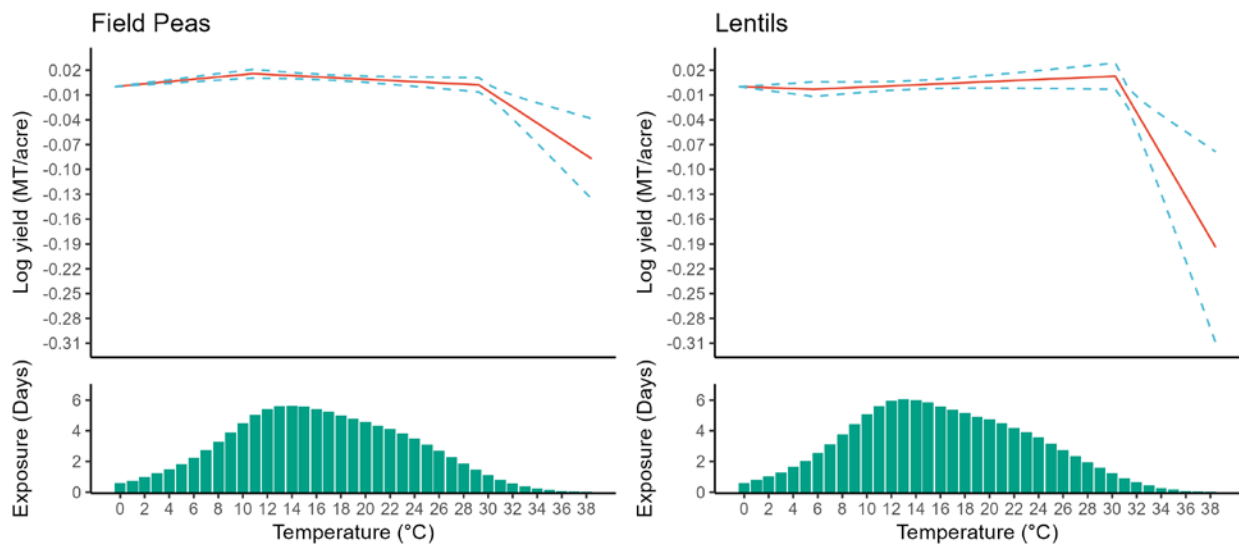
The results from estimating the preferred piecewise linear model are reported in Table B.7. Log yield for both crops was regressed on the three degree day variables, freeze exposure, precipitation and its square, and a linear time trend. Cultivar and location fixed effects were also included. An additional degree day of extreme heat results in a 1.0% yield reduction for field pea and a 2.6% yield reduction for lentil. For field pea, an additional day of freeze exposure reduces yield by 3.5%. Freeze exposure was found to be positive for lentils, but this coefficient is not statistically significant. Precipitation was found to have positive effects for both field pea and lentil, however, excess water had negative effects on both crops as indicated by the precipitation squared coefficients.

Out-of-sample comparisons were made to assess the predictive capability of the preferred piecewise linear model and additional models (average temperature and average minimum and maximum temperatures). The results in Table B.8 show that all models, apart from the average temperature model for field pea, reduce the root mean squared error relative to the baseline model with no weather information.

Figure 2.2 shows the response of crop yield to temperature exposure is nonlinear and heterogeneous by crop. For field pea, additional days of extreme heat (above 29°C) and additional degree days between 12-29°C result in yield reductions while additional degree days between 0-12°C increases yield. Additional degree days between 0-6°C and of extreme heat

(above 30°C) result in lentil yield reductions and additional degree days between 6-30°C increases yield.

Figure 2.2. Nonlinear temperature-yield relationship for field peas and lentils.

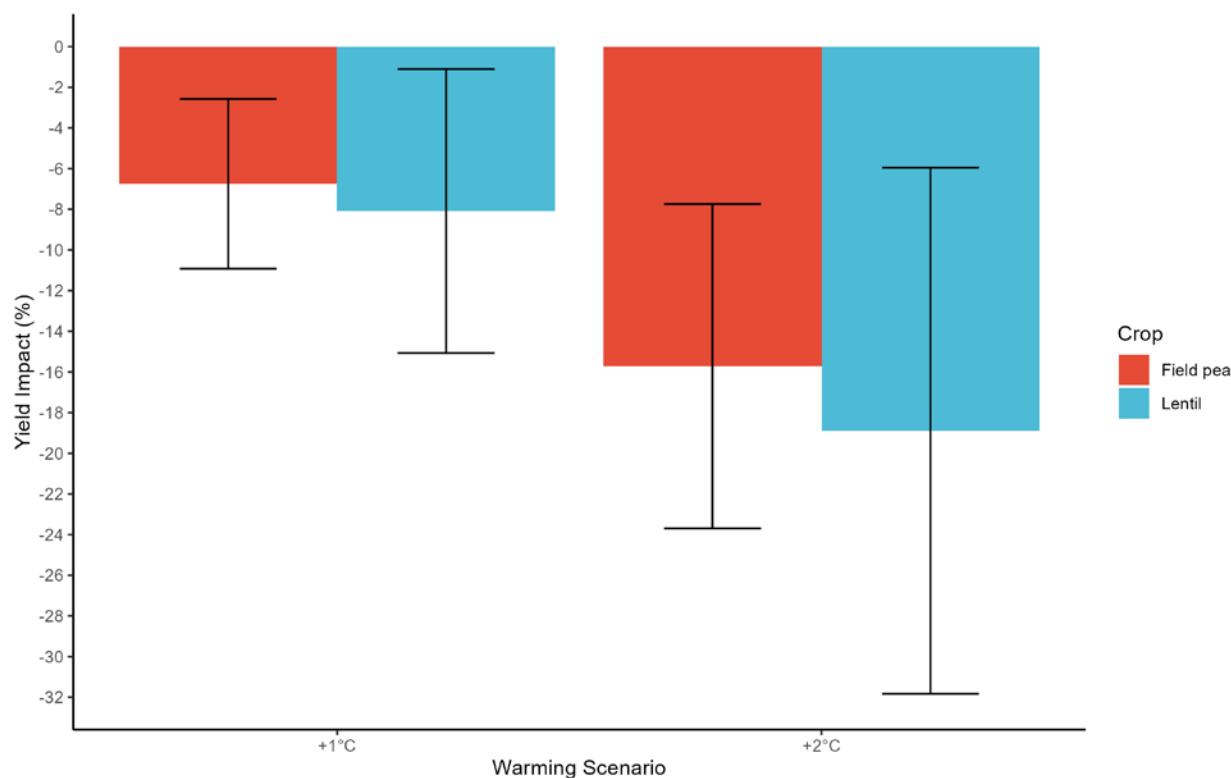


Notes: Graphs at the top of each frame display changes in log yield that occur if the crop is exposed for one day to a particular 1°C temperature interval. Dashed lines show 95% confidence intervals using robust standard errors clustered by year. Histograms at the bottom of each frame display the average temperature exposure among all locations in the data.

2.3.3 Yield Impacts Under Uniform Warming Scenarios

To examine the overall impact of these varying effects, yield outcomes were predicted across uniform temperature changes from +1 and +2°C. Figure 2.3 shows that warming scenarios of +1 and +2°C results in net yield reductions for both crops. Under a +1°C warming scenario, field pea yield decreases by 6.8% while lentil yield decreases by 8.1%. A +2°C warming scenario results in a 15.7% reduction for field peas and 19.0% for lentils. Although warmer temperatures reduce exposure to damaging freeze, the effects of extreme heat persist and result in a net negative effect on yield. These reductions in yield are less severe than the estimated 28.4% to 57.8% yield reduction on Canadian barley, canola, oats, and wheat reported by Tolhurst and Ker (2025). However, field pea and lentil losses are more severe than those associated with corn and soybean losses which range from no change to a 5.2% reduction (Tolhurst and Ker 2025) and hard red spring wheat which range from a 1.0% to 13.2% reduction in Manitoba (Carew et al. 2018).

Figure 2.3. Warming impacts on field pea and lentil yield across uniform changes in temperature.



Notes: Estimated warming impacts are given as a percent change in yield relative to historical climate. Error bars show 95% confidence intervals using robust standard errors clustered by year.

2.3.4 Quality Impacts Under Uniform Warming Scenarios

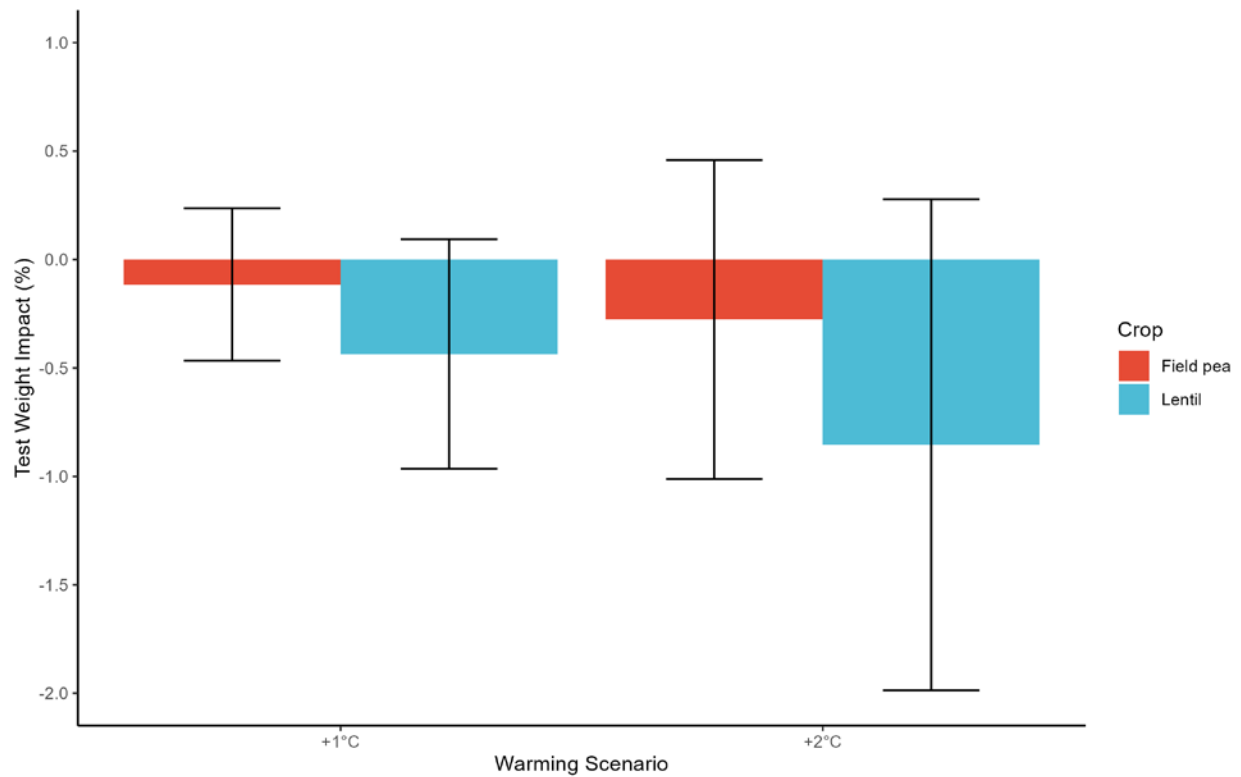
In addition to yield, we estimated the warming impacts on measures of quality, specifically, test weight and protein content. Field pea test weight ranged from 60.0-64.8 lb/acre, and lentil test weight ranged from 58.1-64.2 lb/acre as shown in Table B.9. Figure B.6 shows the spatial and temporal variation of field pea and lentil test weight. Due to limited lentil protein data, the warming impacts were estimated for field pea protein only. Table B.10 shows protein content by location which ranges from 18.2-26.8%, and Figure B.7 shows the variation of field pea protein.

Using the optimal temperature thresholds identified in Tables B.5 and B.6, Equation 2.1 was estimated again for test weight and protein. Table B.11 shows the results from estimating the

preferred piecewise linear model for test weights and protein content. Extreme heat has a negative effect on field pea test weight and a positive effect on lentil test weight, however, the temperature effects on test weight were not significant. For field peas, an additional degree day of extreme heat results in a 0.2% increase in protein content. We also find evidence that breeding efforts have increased pea protein annually by 0.6%.

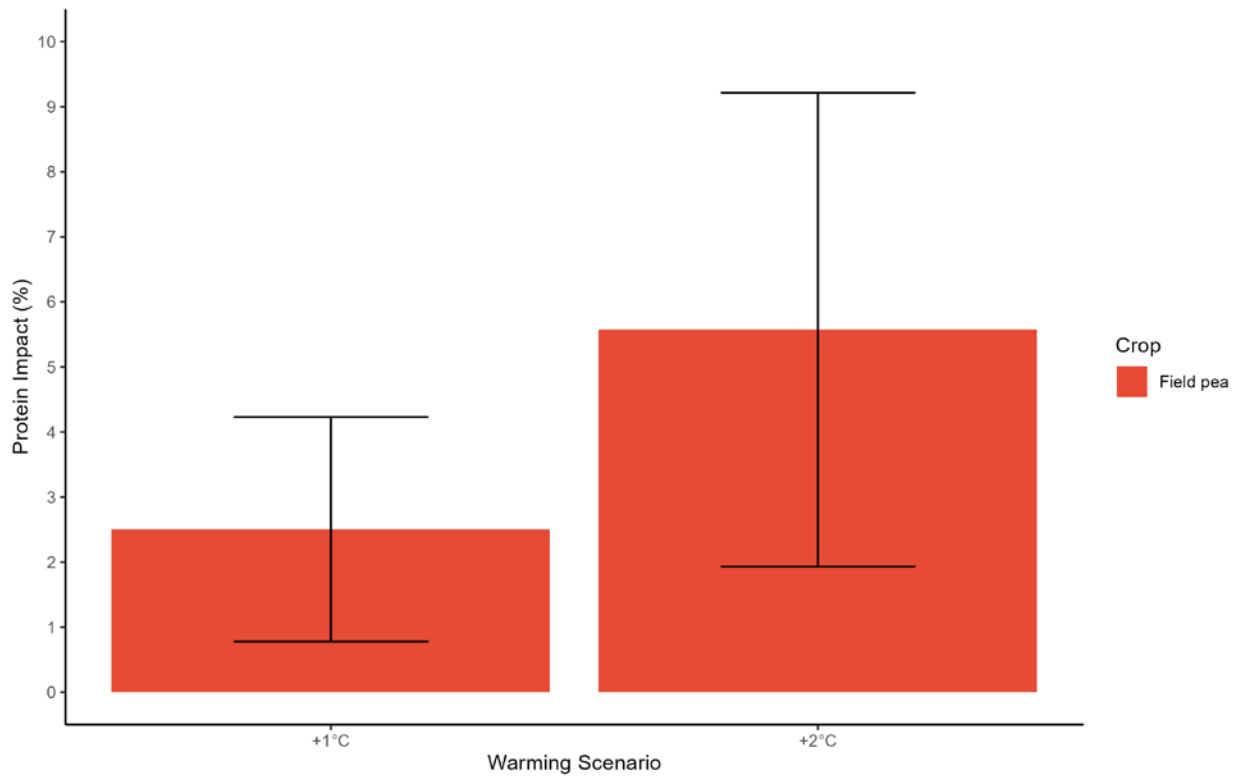
The overall warming impacts on field pea and lentil test weights are small and negative as shown in Figure 2.4. Under a +1°C warming scenario, field pea test weight decreases by 0.1% while lentil yield decreases by 0.4%. A +2°C warming scenario results in a 0.3% reduction for field peas and 0.9% for lentils. Overall, these findings suggest that warming has a small negative effect on field pea and lentil test weights. Figure 2.5 shows that warming has a net positive impact on field pea protein content. Under a +1°C warming scenario, protein content increases by 2.5% and a +2°C increases protein content by 5.6%. These results suggest that extreme heat has the opposite effect on yield and protein content in field peas. This is consistent with the agronomic literature which has found that higher temperatures lead to higher protein content (Walter et al. 2022) and other studies that have reported negative correlations between field pea yield and protein (Daba and Morris 2022; Franck et al. 2024).

Figure 2.4. Warming impacts on field pea and lentil test weight across uniform changes in temperature.



Notes: Estimated warming impacts are given as a percent change in test weight relative to historical climate. Error bars show 95% confidence intervals using robust standard errors.

Figure 2.5. Warming impacts on field pea protein across uniform changes in temperature.



Notes: Estimated warming impacts are given as a percent change in protein relative to historical climate. Error bars show 95% confidence intervals using robust standard errors.

2.4 Discussion

The impact of climate change at high latitudes remains a topic of debate. We contribute to this discussion by constructing a novel cool-season pulses field trial dataset to examine the effects of warming on field pea and lentil in the high latitudes of North America. Overall, our findings suggest that future warming scenarios will have detrimental effects on field pea and lentil yields without adaptation. Although pulse crops are generally perceived as being resilient to heat stress, we find that extreme heat does result in yield losses. We identified an extreme heat threshold of 29°C for field peas and 30°C for lentils. An additional degree day above the extreme heat thresholds results in a 1.0% reduction in yield for field peas and 2.6% reduction for lentils.

The net effect of warming on yield and quality vary in magnitudes and directions. The net warming impact on field pea and lentil yields is negative (-18.9% to -6.8%). The impacts of warming on field pea protein content are moderately positive (+2.5% to +5.6%) while the effects on field pea and lentil test weight are small and negative (-0.9% to -0.1%). This suggests that there may be opportunities to offset negative yield impacts on farm revenue by constructing price premiums for field peas with elevated protein content (Mohammed et al. 2018; Franck et al. 2024). Additionally, breeding effects and cultivar recommendations could be more tailored to the target market (i.e., peas for starch versus protein extraction) (Tao et al. 2017; Daba and Morris 2022).

Gains in productivity may be diminished through the impacts of climate change, requiring large investments in public research and development (Ortiz-Bobea et al. 2025). Improvements in cultivar genetics are an important climate change adaptation strategy that requires breeding program investment (Howden et al. 2007; Atlin, Cairns and Das 2017). Historically, these investments have resulted in increased productivity and planted acres of pulse crops in the U.S. Northern Plains and western Canada (Bueckert and Clarke 2013; Bolek and Gray 2019; Carew, Florkowski and Zhang 2013). However, our results suggest that existing varieties are not robust to heat stress and genetic traits that improve heat resilience should be prioritized to maintain (or increase) productivity.

Chapter 3 - Heterogeneous Effects of Yield and Quality for Herbicide Tolerant Lentil Varieties

3.1 Introduction

Weeds are a significant biotic stressor globally causing up to 34% of crop losses—equivalent to the losses from pathogens (16%) and animal pests (18%) combined (Oerke 2006). Aside from yield losses, weed interference can decrease grain quality, interfere with harvesting, and increase input costs associated with weed control (Soltani et al. 2017). In the United States and Canada, crops with traits for herbicide tolerance (HT) and chemical herbicides are the primary tools used for weed control (Brunharo et al. 2022). Since their commercialization in the mid-1990s, HT crops have improved yield levels and facilitated the adoption of conservation practices such as no till (Green 2012; Perry, Moschini and Hennessy 2016; Claassen et al. 2018; Dong et al. 2024). Traits for HT have been developed through either conventional breeding (e.g., mutagenesis) or genetic engineering (GE) techniques. Genetically modified (GM) crops are the most popular HT crop trait technologies (GM-HT) in North America. In the U.S., 90% of corn, 96% of soybean, and 93% of cotton acres are planted with varieties containing at least one GM-HT trait (USDA ERS 2025). In Canada, 95% of canola, 81% of soybean, and 88% of corn acres are planted with varieties containing at least one GM-HT trait (Danielson and Watters 2023). Notably, GM technology has generally been limited to crops grown for animal feed, fuel, or fiber due to concerns regarding unforeseen human and environmental risks (Herring and Paarlberg 2016; Smyth 2017).

For crops that are more commonly used for human food consumption, such as wheat, lentil, and rice, traits for HT have been introduced via conventional breeding methods. The most popular non-GM-HT crops have traits for imidazolinone (IMI) resistance and are sold under the

brand Clearfield (Tan et al. 2005; Mallory-Smith and Sanchez Olguin 2011). The adoption rates for Clearfield crops are less than those of GM-HT crops although the reporting on Clearfield adoption is limited. For example, in Canada, Clearfield wheat varieties only account for less than 2% of insured planted wheat acres (Brunharo et al. 2022; Canadian Grain Commission 2024a). In the U.S. mid-South, 40% of the long-grain rice acres plant Clearfield varieties (Durand-Morat, Nalley and Thoma 2018; Durand-Morat and Nalley 2019). To our knowledge, lentil acres in Canada have the highest Clearfield adoption rate in North America with over 70% of insured lentil acres planting Clearfield in 2024 (Canadian Grain Commission 2024a).³ Although Clearfield lentil adoption in the U.S. is unknown, it may be reasonable to assume that it is lower than in Canada due to Clearfield seed cost being more expensive in the U.S. (Bourgault et al. 2024).

Lentils are an important source of protein and nutrients for individuals in low- and middle-income countries (Joshi and Rao 2016) and are more frequently being consumed by those in high-income countries in the form of enriched protein foods and plant-based proteins (Khazaei et al. 2019; Troya et al. 2022; Panescu et al. 2023). In the semi-arid region of western Canada and the Northern Plains of the U.S., lentil is commonly grown in a cereal-oilseed rotation under dryland conditions (Miller et al. 2002). This region of North America has become a globally relevant producer of lentils, producing 38% of the world supply and contributing to 54% of the export market (FAO 2023). Over the past two decades, harvested lentil acres in Canada have doubled, and in 2024, 3.6 million and 556,000 acres were harvested in Saskatchewan and Alberta, respectively (Statistics Canada 2025). In the U.S., acreage has more than doubled with acres expanding mainly in Montana and North Dakota where 690,000 and 162,000 acres were

³ In 2024, 86% of lentil acres were insured (Canadian Grain Commission 2024a; Statistics Canada 2025).

harvested in 2024, respectively (USDA NASS 2025). This expansion in production is attributed to both genetic and agronomic improvements in lentil over the past several decades (Muehlbauer et al. 2006; Siddique et al. 2012). Including a lentil crop in a cereal-oilseed rotation provides several benefits such as improved soil quality, reduced disease incidence, and nitrogen fixation which reduces the amount of fertilizer required (Krupinsky et al. 2002; Zentner et al. 2002; Lupwayi and Kennedy 2007; Burgess, Miller and Jones 2012).

On the other hand, lentil is particularly susceptible to weed infestation due to its short stature, slow development, and sparse canopy (Yenish et al. 2009; Brunharo et al. 2022). Management practices such as higher plant densities improve the ability of lentil to compete with weeds (McDonald, Hollaway and McMurray 2007; Baird, Shirtliffe and Walley 2009). There are limited chemical weed control options due to lentil's sensitivity to herbicides and few herbicides control for both grasses and broadleaf weeds (Wall and McMullan 1994). Metribuzin is commonly used for broadleaf weed control (Cessna 1998); however, because of its phytotoxicity, it must be applied early in the growing season and crop injury may be exacerbated if growing conditions are stressful (e.g., drought, heavy rain, high temperatures, or freeze) (Bogdan n.d.).

To improve weed control, the first Clearfield lentil varieties with IMI resistance were commercialized in 2007. IMI herbicides control many grass and broadleaf weeds and can be applied to a lentil crop during a wider time window in the growing season without crop injury. BASF's Clearfield IMI resistant trait is bred into lentil varieties developed by the University of Saskatchewan Crop Development Center (CDC). Since Clearfield is bred into CDC varieties, which are developed using check-off levies collected by the Saskatchewan Pulse Growers Association, seed sales of these varieties outside Saskatchewan are subject to royalty fees including seeds sold in the U.S. (Bolek and Gray 2019). Thus, another open question is whether

the benefits associated with HT lentil adoption are revenue positive through increased yield and/or quality or are cost reducing through less input requirements. While our data preclude us from analyzing profitability directly, we can focus on both yield and quality outcomes thereby providing insights on production efficiencies.

In this study, we investigate the HT effect on lentil quantity (yield) and quality (test weight) in the U.S. and Canada. Variety trial data that includes over 6,600 observations from 2001 to 2023 is used to disentangle the relative output effects between conventional and HT lentil. Our main findings reveal the heterogeneous effects of HT on lentil output. First, we find that HT results in a yield penalty, decreasing lentil yield by 4.15%. Second, HT increases test weight by 0.52%. Third, under weather conditions more conducive to weed interference early in the growing season, HT increases yield by 3.44% for each day of extreme heat. Later in the growing season when weed interference impacts lentil quality, HT increases test weight by 0.08% for each additional day of extreme heat. Taken together, HT technology in lentil provides risk reducing production benefits.

The rest of the paper is organized as follows. The next section discusses the data and model estimation. The third section details the results as well as a series of robustness checks. Lastly, in the fourth section we offer some concluding remarks.

3.2 Methods

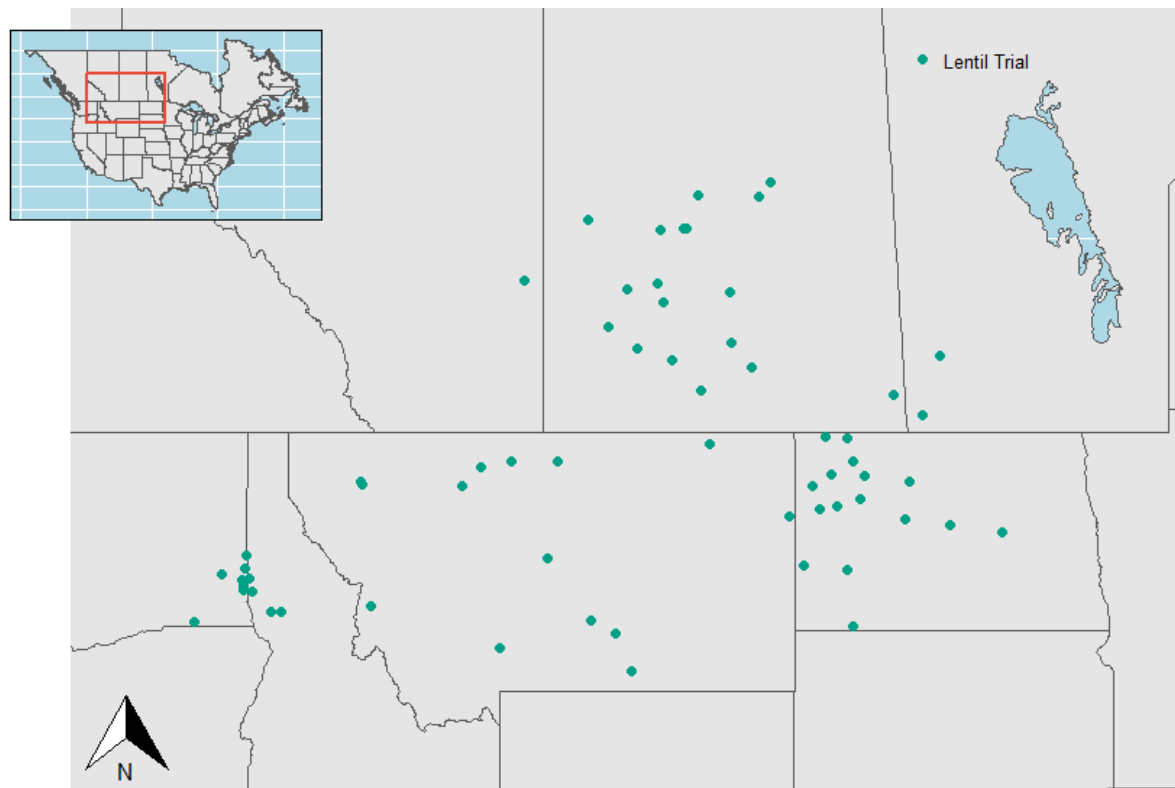
Two main sources of data were used in the study: variety trial and daily weather data. Both data sets are described in the subsections below. To proxy for weed pressure, weather variables were constructed for two distinct time windows, the critical period for weed control (CPWC) and post CPWC. The CPWC for lentil and the procedure employed to estimate the preferred model are also detailed in the subsections below.

3.2.1 Variety Trial Data

North American pulse variety trial data was compiled and discussed in Chapter 2. Data was collected from publicly available field trial reports from the largest producing lentil provinces in Canada (Manitoba and Saskatchewan) and states in the U.S. (Idaho, Montana, North Dakota, and Washington).⁴ Figure 3.1 shows the trial locations included in the data. In Canada, these trials were conducted through producer associations while trials in the U.S. were conducted through university experiment stations. In both cases, these trials were conducted using randomized control block design with the explicit goal of providing producers with independent and unbiased information on variety performance. Data was collected for lentil yield and test-weight at the variety-location-year level, in addition to variety characteristics such as market type and whether a variety was HT. To ensure a direct comparison between varieties, only market types with both conventional and HT varieties were included in-sample (e.g., large red, small red, extra small red, large green, medium green, small green, French green, green cotyledon, and Spanish brown). Additional information on agronomic practices including planting date, harvest date, irrigation, tillage, and previous crop were collected at the location-year level when available. All trials were assumed to be dryland unless irrigation was indicated. Irrigated field trials were not included in-sample.

⁴ With the exception of Alberta because actual yield by location was not publicly available. Alberta Pulse Growers variety trial reports only include percent yield relative to a check variety and were aggregated by soil zone.

Figure 3.1. Map of in-sample dryland lentil trial locations: 2001-2023.



Notes: Data was collected from annual variety trial reports from Canada (Manitoba and Saskatchewan) and the U.S. (Idaho, Montana, North Dakota, and Washington). Variety trial reports were published by producer associations in Canada and university extension services in the U.S.

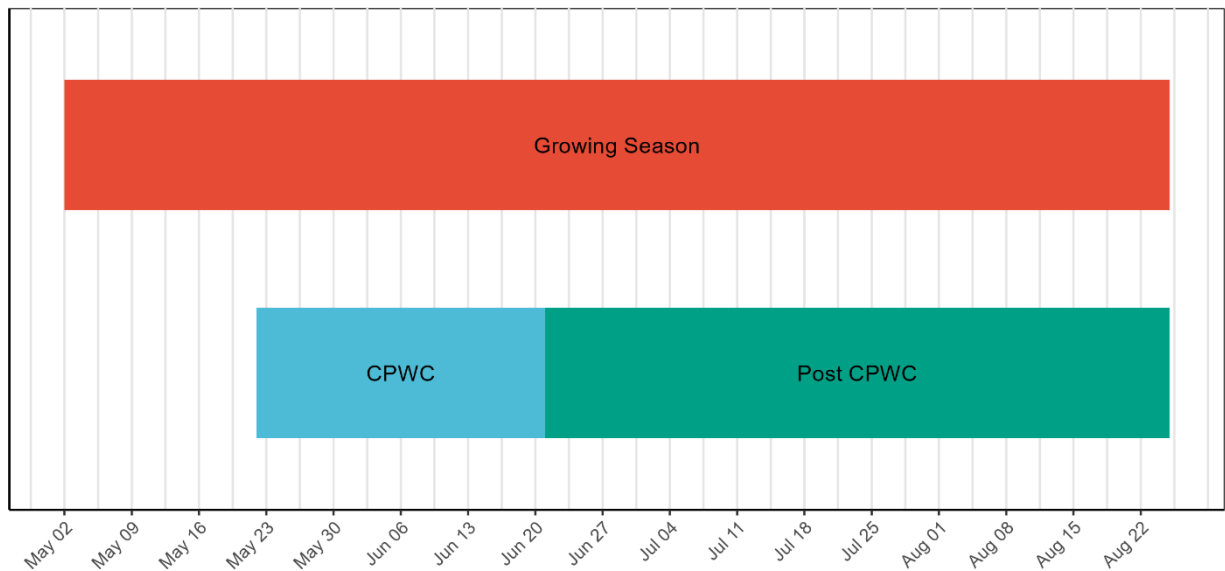
This extensive data included 6,612 observations, spanned 67 locations, 23 years, and included 174 conventional and 27 HT lentil varieties. Each year, the number of trials ranged from two to 34 and the number of cultivars ranged from seven to 70 as shown in Table C.1 in Appendix C. In 2007, the first HT cultivars entered the trials making up 7.0% of the cultivars that year, growing up to 40.4% of the cultivars over time (Table C.1). Tables C.2 and C.3 present summary statistics for lentil yields and test weights, respectively. Average lentil yield was 0.74 MT/a with conventional and HT cultivars yielding 0.69 MT/a and 0.84 MT/a, respectively. Average lentil test weight was 60.71 pounds per bushel (lb/bu) and conventional and HT test weights were 60.83 and 60.48 lb/bu, respectively. There was a substantial amount of variation in lentil yield across locations, cultivars, and years as shown in Figure C.1 with yield increasing

over time. There was also meaningful variation in lentil test weight although test weight was relatively more stable over time (Figure C.1).

3.2.2 Critical Period for Weed Control

The CPWC is the period when a crop must be kept weed free to prevent significant yield loss due to weed interference (Knezevic et al. 2002). For lentil, this period typically begins at the five-node stage and ends at the ten-node stage (Fedoruk, Johnson and Shirtliffe 2011) with a new node emerging every four to five days during the growing season (Saskatchewan Pulse Growers 2023). Therefore, we defined the CPWC as beginning on day 20 and ending on day 50 after the observed planting date. Figure 3.2 shows a timeline using the average growing season in the data as an example. The average seeding and harvest dates observed in the data were May 2 and August 25, respectively. As mentioned above, the seeding and harvest days were typically noted in the trial reports. For location-years missing these dates, seeding date predicted values were obtained by regressing the seeding date on the location longitude and latitude with year fixed effects (or a year trend). Similarly, harvest date predicted values were obtained by regressing the harvest date on the location longitude, latitude, and planting date with year fixed effects (or a year trend). The average CPWC started on May 22 and ended on June 21. The average post CPWC was June 22 through August 25 or day of harvest. The seeding and harvest dates, as well as the CPWC and post CPWC, varied at the location-year level.

Figure 3.2. Timeline of average lentil growing season, critical period for weed control (CPWC), and post CPWC.



Notes: The average growing season observed in the data was May 2-August 25. The CPWC began on day 20 and ended on day 50 after planting. The average CPWC observed was May 22-June 21, and the remainder of the growing season was defined as post CPWC. All the dates varied at the location-year level in the data.

3.2.3 Weather Data

To explore some potential nuances of HT technology, the variety trial data was combined with location-year specific weather data to proxy for weed pressure. Environmental factors can either promote weed growth or create stressful conditions that make a crop less competitive. For example, heat (e.g., temperatures above 30°C) increases the growth rate of many weed species while warmer temperatures and drought can reduce crop competitiveness (Patterson 1995; Guo and Al-Khatib 2003; Sarangi et al. 2016). Remaining agnostic to the precise mechanism by which weather impacts weeds/lentil, weather variables for precipitation, beneficial lentil degree days, extreme heat, and freeze were created to assess the heterogeneous effects of HT.

Gridded daily maximum temperatures, minimum temperatures, and precipitation during the growing season for each location were obtained from Daymet at the 1x1 kilometer level (Thornton et al. 2022). The temperature variables were calculated as degree days spent between

6-30°C and degree days above 30°C during the CPWC and post CPWC. Degree days 6-30°C captured the temperatures that were beneficial to lentil growth and development (i.e., increase lentil competitiveness against weeds). In contrast, degree days above 30°C captured temperatures that were detrimental to both lentil yield and test weight due to heat stress (i.e., decrease lentil competitiveness) (Chapter 2). The temperature variables were constructed at the daily level using sinusoidal approximation of temperature exposure between the observed temperature minimum and maximum and then summed across the CPWC and post CPWC time windows. Daily precipitation was also summed across the CPWC and post CPWC. Figure C.2 shows the substantial amount of variation among the weather variables. We also observed meaningful differences between weather during the CPWC and post CPWC in the data.

3.2.4 Model Estimation

A fixed effects regression model was employed to estimate lentil yield performance for cultivar i at location l in year t :

$$(3.1) \quad y_{ilt} = \alpha_{lt} + \beta HT_i + \varepsilon_{ilt}$$

where y_{ilt} was yield measured in MT/acre for lentil type i , at location l , in year t . α_{lt} was the location-by-year fixed effects. The location dimension of the fixed effect controlled for factors such as soil type, climate, and location management practices while the year dimension controlled for changes to management practices over time. By crossing the location-by-year fixed effects, we were able to control for factors that vary at the location-year level such as weather, disease, pest pressure, and spatial differences in management practices. HT_i was an indicator variable that took on a value of one if the cultivar contained a trait for HT, and ε_{ilt} was the error term that captured unobservable variables. β was the primary effect of interest and was

the HT effect on lentil yield. Standard errors were clustered by year to account for the widest possible range of spatial correlation across all locations.

To examine the HT effects on quality, we replaced the dependent variable, y_{ilt} , with test weight measured in lb/bu. Test weight is a measure of a grain's density, or the weight of the grain packed in a specific volume (Canadian Grain Commission 2024b). Previous work has used it as a proxy for quality (Ko and Ramsey 2022). Thus, β becomes the HT effect on lentil quality.

Next, the model in Equation 3.1 was extended to include weather variables w_{lt} at the location-year level for two distinct time windows. By constructing proxy variables for weed pressure, we can disentangle the effects of HT under weather conditions more or less conducive to weed interference. The following regression model was estimated for both lentil yield and test weight:

$$(3.2) \quad y_{ilt} = \alpha_{lt} + \beta HT_i + \gamma HT_i w_{lt} + \varepsilon_{ilt}.$$

There was limited information in the literature regarding weather variability and weed pressure in lentil production systems. Therefore, we estimated Equation 3.2 for each weather variable separately (e.g., precipitation, medium degree days, high degree days, and freeze for the CPWC and post CPWC windows). In addition to β the HT effect on lentil yield, estimating Equation 3.2 gives the additional parameter estimate of γ , the effect of HT on lentil yield under conditions favorable/unfavorable to weed pressure. In addition to yield, Equation 3.2 is also estimated for test weight.

3.3 Results

3.3.1 HT Effect on Yield

Variety trial data was used to estimate the effect of HT technology on lentil yield and test weight (Equation 3.1). The nuances of HT were assessed further by interacting the HT variable

with daily weather information during the CPWC and post CPWC (Equation 3.2). Table 3.1 reports the effects of HT on lentil yield across several dimensions. We find a significant yield difference between conventional and HT varieties. On average, HT varieties decrease lentil yield by 4.15% ($P < 0.01$) (Table 3.1, model 1). Interacting HT with extreme heat (DD High) during the CPWC results in a positive effect on yield of 3.44% ($P < 0.01$) with an overall HT yield penalty of 5.33% ($P < 0.01$) (Table 3.1, model 4), similar to the homogenous effect. This result suggests that HT improves lentil yield outcomes when early season weed interference is high. Incorporating additional terms such as HT x Post CPWC DD High (model 10) and HT x CPWC Precipitation, HT x Post CPWC Precipitation, and HT x Post CPWC DD High (model 11) resulted in a stable HT x CPWC DD High estimate between 3.01-3.18% ($P < 0.01$) (Table 3.1). The interaction of HT with precipitation (model 2), medium degree days (model 3), and freeze (model 5) during the CPWC resulted in statistically insignificant effects and all interaction terms post CPWC (models 6-9) were not significant ($P > 0.10$) (Table 3.1).

Table 3.1. Effects of HT technology on log lentil yield (MT/a) across several dimensions.

Variables	1	2	3	4	5	6	7	8	9	10	11
HT	-0.0415*** (0.0071)	-0.0445** (0.0170)	-0.1667* (0.0859)	-0.0533*** (0.0072)	-0.0490*** (0.0078)	-0.0054 (0.0251)	-0.0383 (0.0786)	-0.0566*** (0.0094)	-0.0420*** (0.0068)	-0.0614*** (0.0089)	-0.0699 (0.0439)
HT x CPWC Precipitation		0.0004 (0.0015)									0.0030 (0.0018)
HT x CPWC DD Medium			0.0004 (0.0003)								
HT x CPWC DD High				0.0344*** (0.0035)						0.0301*** (0.0047)	0.0318*** (0.0075)
HT x CPWC Freeze					0.0680 (0.0426)						
HT x Post CPWC Precipitation						-0.0033 (0.0020)					-0.0015 (0.0021)
HT x Post CPWC DD Medium							0.0000 (0.0001)				
HT x Post CPWC DD High								0.0031 (0.0018)		0.0020 (0.0021)	0.0020 (0.0023)
HT x Post CPWC Freeze									0.0195 (0.0252)		
Year-Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.8688	0.8688	0.869	0.8691	0.8689	0.8689	0.8688	0.8689	0.8688	0.8691	0.8692
Observations	6,596	6,596	6,596	6,596	6,596	6,596	6,596	6,596	6,596	6,596	6,596

Notes: Model 1 is the base scenario of a homogeneous HT effect on yield. Models 2-5 interacts precipitation, DD medium, DD high, and freeze during the CPWC with the HT variable. Models 5-9 interacts precipitation, DD medium, DD high, and freeze during the post CPWC with the HT variable. Model 10 interacts the HT variable with DD high during the CPWC and post CPWC. Model 11 interacts the HT variable with DD high and precipitation during the CPWC and post CPWC. Standard errors are in parentheses and are clustered by year. *, **, and *** denote statistically significance at the 10%, 5%, and 1% level, respectively.

These results suggest that there was an overall yield penalty associated with planting a HT variety. However, for each additional degree day of extreme heat during the CPWC, the HT effect on yield was positive, nearly canceling out the yield penalty. This was consistent with two independent findings others have documented in the literature. The first being that the early establishment of weeds can result in weeds having a competitive advantage over crops, thereby reducing yield (Knott and Halila 1988; Kropff, Weaver and Smits 1992; Bosnic and Swanton 1997). The second is that extreme heat increases the competitiveness of weeds in production systems and can further reduce yield if complete weed control is not achieved (Patterson 1995; Guo and Al-Khatib 2003; Sarangi et al. 2016; Landau, Hager and Williams 2021; Landau, Hager and Williams 2022).

3.3.2 HT Effect on Test Weight

Table 3.2 reports the effects of HT on lentil quality (test weight) across several dimensions. HT varieties increase lentil test weight by 0.52% ($P < 0.01$) (Table 3.2, model 1). Interacting HT with extreme heat (DD High) post CPWC results in a positive effect on test weight of 0.08% ($P < 0.01$) (Table 3.2, model 8). This suggests that HT improves test weight outcomes when late season weed interference is high. Incorporating additional terms such as HT x CPWC DD High (model 10) and HT x CPWC Precipitation, HT x CPWC DD High, and HT x Post CPWC Precipitation (model 11) resulted in a stable HT x Post CPWC DD High estimate between 0.07-0.08% ($P < 0.01$) (Table 3.2). The interaction of HT with freeze during the CPWC (model 5) increases test weight by 0.70% ($P < 0.05$) and precipitation post CPWC (model 6) decreased test weight by 0.04% ($P < 0.05$) (Table 3.2). The interaction of HT with precipitation (model 2), medium degree days (model 3), and high degree days (model 4) during the CPWC

and medium degree days (model 7) and freeze (model 9) post CPWC resulted in statistically insignificant effects ($P > 0.10$) (Table 3.2).

Table 3.2. Effects of HT technology on log lentil test weight (lb/bu) across several dimensions.

Variables	1	2	3	4	5	6	7	8	9	10	11
HT	0.00524*** (0.00166)	0.00844*** (0.00230)	-0.00269 (0.01037)	0.00470** (0.00187)	0.00447** (0.00183)	0.00946** (0.00351)	0.02200 (0.01944)	0.00153 (0.00162)	0.00518*** (0.00170)	0.00155 (0.00177)	0.00290 (0.00292)
HT x CPWC Precipitation		-0.00038 (0.00032)									-0.00005 (0.00030)
HT x CPWC DD Medium			0.00003 (0.00004)								
HT x CPWC DD High				0.00157 (0.00133)						-0.00012 (0.00158)	-0.00024 (0.00154)
HT x CPWC Freeze					0.00704** (0.00289)						
HT x Post CPWC Precipitation						-0.00038** (0.00018)					-0.00007 (0.00021)
HT x Post CPWC DD Medium							-0.00002 (0.00002)				
HT x Post CPWC DD High								0.00076*** (0.00015)		0.00077*** (0.00013)	0.00073*** (0.00014)
HT x Post CPWC Freeze									0.00248 (0.00224)		
Year-Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.4965	0.4967	0.4967	0.4966	0.4968	0.4969	0.4968	0.4984	0.4965	0.4984	0.4984
Observations	5,116	5,116	5,116	5,116	5,116	5,116	5,116	5,116	5,116	5,116	5,116

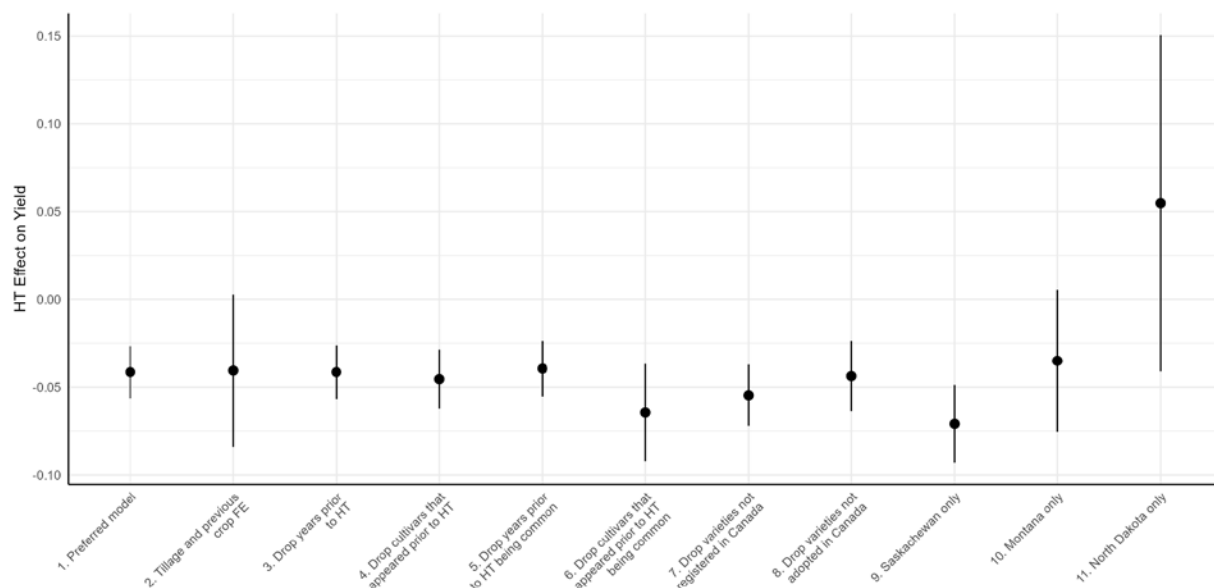
Notes: Model 1 is the base scenario of a homogeneous HT effect on test weight. Models 2-5 interacts precipitation, DD medium, DD high, and freeze during the CPWC with the HT variable. Models 5-9 interacts precipitation, DD medium, DD high, and freeze during the post CPWC with the HT variable. Model 10 interacts the HT variable with DD high during the CPWC and post CPWC. Model 11 interacts the HT variable with DD high and precipitation during the CPWC and post CPWC. Standard errors are in parentheses and are clustered by year. *, **, and *** denote statistically significance at the 10%, 5%, and 1% level, respectively.

These results suggest that HT varieties have small positive effects on test weight. This is consistent with other findings documenting that weed interference later in the growing season competes with lentil pod and seed development, reducing seed size and quality (Smitchger, Burke and Yenish 2012). The interaction effects between HT x CPWC Freeze and HT x Post CPWC Precipitation on test weight were more difficult to interpret since there is less literature documenting the interactions between weed pressure and quality.

3.3.3 Robustness Checks

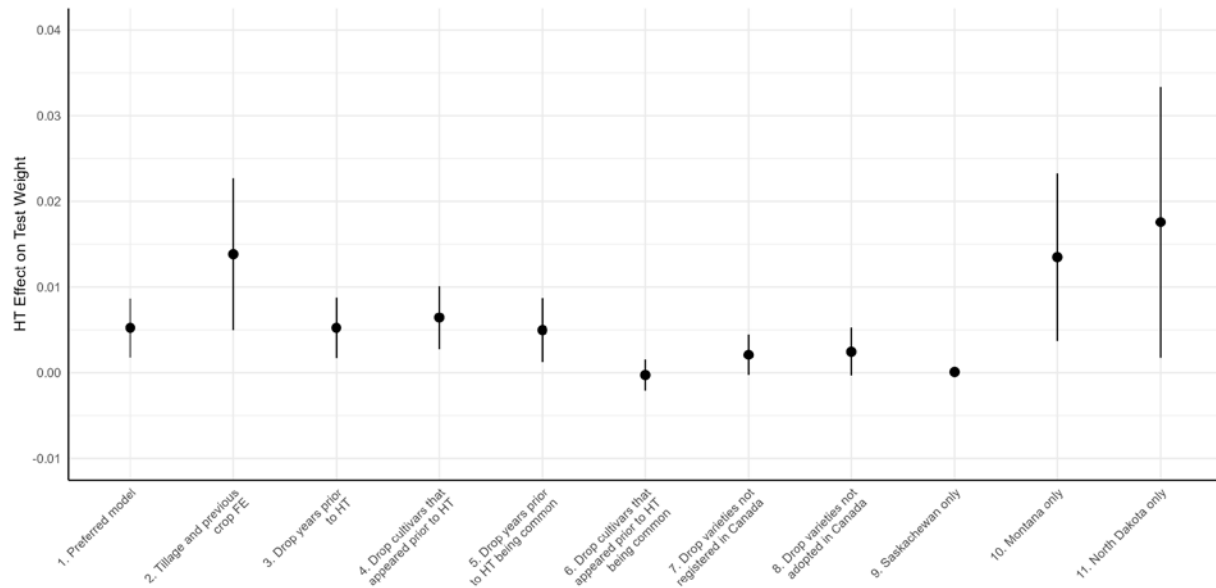
We scrutinize our results by conducting a series of robustness checks. Figures 3.3 and 3.4 show the point estimates for the HT effect on yield and test weight, respectively, obtained from alternative specifications. We generally conclude that the HT effect on yield of -0.042 ($P < 0.01$) (Figure 3.3, model 1) and the HT effect on test weight of 0.005 ($P < 0.01$) (Figure 3.4, model 1) were robust across various specifications.

Figure 3.3. Point estimates for the HT effect on yield from alternative specifications.



Notes: Point estimates are reported at the 95% confidence interval with standard errors clustered by year. The preferred model and alternative specifications are described in more detail in the text.

Figure 3.4. Point estimates for the HT effect on test weight from alternative specifications.



Notes: Point estimates are reported at the 95% confidence interval with standard errors clustered by year. The preferred model and alternative specifications are described in more detail in the text.

Both tillage practices and crop rotations can impact weed pressure and crop yield. To investigate if these management practices change the HT effect, tillage and previous crop fixed effects were incorporated into Equation 3.1 and the model was re-estimated. In the data, tillage was an indicator variable that took on a value of zero if trials were conducted on no-till plots or one if trials were conducted on plots that were tilled. Previous crop indicates the crop that was grown on that plot before the lentil trial was conducted (e.g., barley, spring wheat, winter wheat, etc.). The inclusion of tillage and previous crop fixed effects resulted in a HT effect on yield of -0.04 ($P < 0.10$) (Figure 3.3, model 2) and a HT effect on test weight of 0.01 ($P < 0.01$) (Figure 3.4, model 2). From this we can conclude that the HT effect obtained from the preferred model was robust to these management practices.

The remainder of the robustness checks consider various subsets of the data. We consider subsets that focused on side-by-side comparisons of conventional and HT varieties in the trials by dropping the years prior to HT entering the trials (2007) (model 3) and prior to HT becoming

common in trials (2010) (model 5). We also filtered out older cultivars that first appeared prior to HT (model 4) and prior to HT being common in the trials (model 6). The HT effect on yield (Figure 3.3) and test weight (Figure 3.4) remained stable across these alternatives.

Next, we dropped varieties in the data that were not registered in Canada and varieties that were not adopted in Canada between 2008-2023. Both checks function to filter out more experimental varieties that entered the trials and focus on varieties that were more likely to be commercially available. The former functions to compare HT varieties with conventional varieties that have successfully been registered in Canada (i.e., demonstrated an improvement to yield, disease resistance, etc.) while the latter functions to compared HT and conventional varieties that have been adopted by producers. No such registry exists in the U.S., likewise, data on variety adoption rates were unavailable for the U.S. Lentil varieties registered in Canada were obtained from the Canadian Food Inspection Agency (2024). Lentil varieties adopted by insured acres in Canada were obtained from the Canadian Grain Commission (2024a) at the provincial level. The HT effect on yield (Figure 3.3, models 7-8) and test weight (Figure 3.4, models 7-8) remained stable. This further suggests that although variety trial data may include experimental varieties that appear in the trials for a limited number of locations or years, they do not significantly impact the results.

The last set of robustness checks subsets the data into one province (Saskatchewan) and two states (Montana and North Dakota). Manitoba, Idaho, and Washington have less than 700 observations each, thus, we did not subset these states. We observe small differences in the HT yield effects by state including -0.07 ($P < 0.01$) for Saskatchewan, -0.04 ($P < 0.10$) for Montana, and 0.05 ($P > 0.10$) for North Dakota (Figure 3.3, models 9-11). Similar differences in the HT effect on test weight were observed including 0.0001 ($P > 0.10$) for Saskatchewan, 0.0135 ($P <$

0.01) for Montana, and 0.0176 ($P < 0.05$) for North Dakota (Figure 3.3, models 9-11). Overall, the HT effect is robust to alternative specifications and subsets of the data.

3.4 Conclusions

This study documents the heterogeneous effects of HT lentil technology. First, the HT effect impacts lentil quantity and quality differently decreasing yield by 4.2% and increasing test weight by 0.5%. Despite the overall yield penalty, producers may gain utility from the technology through risk protection (i.e., producers have more flexibility with respect to herbicide applications). Second, by interacting HT with weather variables to proxy for weed interference, we uncovered that extreme heat impacts lentil outcomes differently. During the CPWC, HT improves yield outcomes when weed interference is high. Post CPWC, HT improves test weight when weed interference is high. This further suggests that HT varieties have risk reducing benefits on production, and HT technology provides enhanced weed control at different points throughout the growing season.

Our results offer initial insights into a crop-trait technology adopted by Canadian lentil producers. With farm-level data, more credible identification may be achieved. It is possible that the on-farm effects of HT lentil may be greater than those captured here since the management practices used in trial may not be reflective of management practices on-farm. Additionally, the benefits of HT lentil may manifest through changes in herbicide applications that may reduce herbicide costs.

These findings highlight the importance of considering the linkages and compounding effects of biotic and abiotic stress when evaluating the efficacy of agricultural technologies. Climate change is likely to accelerate the growth and expansion of crop pests, diseases, and weeds, particularly in temperate regions at higher latitudes (Rosenzweig et al. 2001; Yang et al.

2024). Moreover, abiotic and biotic stress often occur simultaneously, limiting the opportunities for effective weed control. Our findings suggest that adopting HT lentil technology may be an important climate change adaptation strategy as warmer temperatures at higher latitudes not only impact lentil productivity directly (Chapter 2), but potentially indirectly through increased weed pressure.

References

- Abdulai, A. 2023. "Information acquisition and the adoption of improved crop varieties." *American Journal of Agricultural Economics* 105(4):1049–1062.
- Abrams, S.A., J.L. Albin, P.J. Landrigan, COMMITTEE ON NUTRITION, M.R. Corkins, C.L. Blanco, G.J. Fuchs, P.S. Godoy, T.S. Hannon, C.W. Lindsey, E.S. Rome, A. Bremer, A. Lots, C. Perrine, A. Sant'Anna, C. Funanich, D.L. Burrowes, COUNCIL ON ENVIRONMENTAL HEALTH AND CLIMATE CHANGE, A. Bole, S.J. Balk, L.G. Byron, G.M. Huerta-Montañez, P.J. Landrigan, S.M. Marcus, A.L. Nerlinger, L.H. Patel, R. Philipsborn, A.D. Woolf, L. Zajac, K.A. Gray, J. Briskin, N.G. DeNicola, M. Karwowski, M.H. Ward, and P. Spire. 2024. "Use of Genetically Modified Organism (GMO)-Containing Food Products in Children." *Pediatrics* 153(1):e2023064774.
- Aglasan, S., B.K. Goodwin, and R.M. Rejesus. 2023. "Risk effects of GM corn: Evidence from crop insurance outcomes and high-dimensional methods." *Agricultural Economics* 54(1):110–126.
- Ala-Kokko, K., L. Lanier Nalley, A.M. Shew, J.B. Tack, P. Chaminuka, M.D. Matlock, and M. D'Haese. 2021. "Economic and ecosystem impacts of GM maize in South Africa." *Global Food Security* 29:100544.
- An, H., and R. Carew. 2015. "Effect of climate change and use of improved varieties on barley and canola yield in Manitoba." *Canadian Journal of Plant Science* 95(1):127–139.
- Arthur, L.M., and F. Abizadeh. 1988. "Potential Effects of Climate Change on Agriculture in the Prairie Region of Canada." *Western Journal of Agricultural Economics* 13(2):216–224.
- Atlin, G.N., J.E. Cairns, and B. Das. 2017. "Rapid breeding and varietal replacement are critical to adaptation of cropping systems in the developing world to climate change." *Global Food Security* 12:31–37.
- Baird, J.M., S.J. Shirliffe, and F.L. Walley. 2009. "Optimal seeding rate for organic production of lentil in the northern Great Plains." *Canadian Journal of Plant Science* 89(6):1089–1097.
- Barkley, A.P. 2024. "Social Learning in Wheat Variety Selection: Policy Implications for Wheat Breeding Programs and Variety Adoption." *Working Paper*.
- Barkley, A.P., and L.L. Porter. 1996. "The Determinants of Wheat Variety Selection in Kansas, 1974 to 1993." *American Journal of Agricultural Economics* 78(1):202–211.
- Barrera, A. 2025. "After trade dispute, Mexico officially bans the planting of GM corn." *Reuters*. Available at: <https://www.reuters.com/markets/commodities/after-trade-dispute-mexico-officially-bans-planting-gm-corn-2025-02-26/> [Accessed May 8, 2025].

- Besley, T., and A. Case. 1993. "Modeling Technology Adoption in Developing Countries." *The American Economic Review* 83(2):396–402.
- Bhandari, K., K. Sita, A. Sehgal, A. Bhardwaj, P. Gaur, S. Kumar, S. Singh, K.H.M. Siddique, P.V.V. Prasad, U. Jha, and H. Nayyar. 2020. "Differential heat sensitivity of two cool-season legumes, chickpea and lentil, at the reproductive stage, is associated with responses in pollen function, photosynthetic ability and oxidative damage." *Journal of Agronomy and Crop Science* 206(6):734–758.
- Bheemanahalli, R., R. Sathishraj, J. Tack, L.L. Nalley, R. Muthurajan, and K.S.V. Jagadish. 2016. "Temperature thresholds for spikelet sterility and associated warming impacts for sub-tropical rice." *Agricultural and Forest Meteorology* 221:122–130.
- Bogdan, J. "Herbicide Injury in Pulse Crops." Available at: <https://saskpulse.com/resources/herbicide-injury-in-pulse-crops/> [Accessed June 10, 2025].
- Bolek, K., and R. Gray. 2019. "Intellectual Property Rights and Funding Canadian Pulse Breeding for the 21st Century." Genome Canada.
- Bolger, A.M., H. Poorter, K. Dumschott, M.E. Bolger, D. Arend, S. Osorio, H. Gundlach, K.F.X. Mayer, M. Lange, U. Scholz, and B. Usadel. 2019. "Computational aspects underlying genome to phenome analysis in plants." *The Plant Journal* 97(1):182–198.
- Bosnic, A.C., and C.J. Swanton. 1997. "Influence of barnyardgrass (*Echinochloa crus-galli*) time of emergence and density on corn (*Zea mays*)." *Weed Science* 45(2):276–282.
- Bourgault, M., P.R. Miller, S. Fordyce, P.F. Lamb, J. Holmes, S.T. Koeshall, and P.M. Carr. 2024. "How do roll timing and seeding rate affect lentil yields?" *Crop, Forage & Turfgrass Management* 10(1). Available at: <https://acsess.onlinelibrary.wiley.com/doi/10.1002/cft2.20278> [Accessed May 22, 2025].
- Bowles, T.M., M. Mooshammer, Y. Socolar, F. Calderón, M.A. Cavigelli, S.W. Culman, W. Deen, C.F. Drury, A. Garcia Y Garcia, A.C.M. Gaudin, W.S. Harkcom, R.M. Lehman, S.L. Osborne, G.P. Robertson, J. Salerno, M.R. Schmer, J. Strock, and A.S. Grandy. 2020. "Long-Term Evidence Shows that Crop-Rotation Diversification Increases Agricultural Resilience to Adverse Growing Conditions in North America." *One Earth* 2(3):284–293.
- Brennan, J.P. 1984. "Measuring the Contribution of New Varieties to Increasing Wheat Yields." *Review of Marketing and Agricultural Economics* 52(03):175–195.
- Brookes, G., and P. Barfoot. 2018. "GM crops: global socio-economic and environmental impacts 1996-2016." PG Economics Ltd. Available at: <https://www.pgeconomics.co.uk/>.
- Brown, D., I. Van Den Bergh, S. De Bruin, L. Machida, and J. Van Etten. 2020. "Data synthesis for crop variety evaluation. A review." *Agronomy for Sustainable Development* 40(4):25.

- Brunharo, C.A.C.G., R. Gast, V. Kumar, C.A. Mallory-Smith, B.D. Tidemann, and H.J. Beckie. 2022. "Western United States and Canada perspective: are herbicide-resistant crops the solution to herbicide-resistant weeds?" *Weed Science* 70(3):272–286.
- Bueckert, R.A., and J.M. Clarke. 2013. "Review: Annual crop adaptation to abiotic stress on the Canadian prairies: Six case studies." *Canadian Journal of Plant Science* 93(3):375–385.
- Burgess, M.H., P.R. Miller, and C.A. Jones. 2012. "Pulse Crops Improve Energy Intensity and Productivity of Cereal Production in Montana, USA." *Journal of Sustainable Agriculture* 36(6):699–718.
- Burlig, F., and A.W. Stevens. 2024. "Social networks and technology adoption: Evidence from church mergers in the U.S. Midwest." *American Journal of Agricultural Economics* 106(3):1141–1166.
- Canadian Food Inspection Agency. 2024. "Varieties of Crop Kinds Registered in Canada." Available at: https://active.inspection.gc.ca/netapp/regvar/regvar_lookupe.aspx [Accessed June 9, 2025].
- Canadian Grain Commission. 2024a. "Grain varieties by acreage insured." Available at: <https://grainscanada.gc.ca/en/grain-research/statistics/varieties-by-acreage/> [Accessed May 28, 2025].
- Canadian Grain Commission. 2024b. "Test weight for Canadian grains." Available at: <https://www.grainscanada.gc.ca/en/grain-quality/grain-grading/grading-factors/test-weight-grain.html> [Accessed June 10, 2025].
- Carew, R., W.J. Florkowski, and Y. (Rachel) Zhang. 2013. "Review: Industry levy-funded pulse crop research in Canada: Evidence from the prairie provinces." *Canadian Journal of Plant Science* 93(6):1017–1028.
- Carew, R., T. Meng, W.J. Florkowski, R. Smith, and D. Blair. 2018. "Climate change impacts on hard red spring wheat yield and production risk: evidence from Manitoba, Canada" C. Willenborg, ed. *Canadian Journal of Plant Science* 98(3):782–795.
- Cassman, K.G. 1999. "Ecological intensification of cereal production systems: Yield potential, soil quality, and precision agriculture." *Proceedings of the National Academy of Sciences* 96(11):5952–5959.
- Cessna, A.J. 1998. "Metribuzin residues in lentil following postemergence application." *Canadian Journal of Plant Science* 78(1):167–169.
- Chavas, J., G. Shi, and J. Lauer. 2014. "The Effects of GM Technology on Maize Yield." *Crop Science* 54(4):1331–1335.
- Chiang, H.C. 1973. "Bionomics of the northern and western corn rootworms." *Annual review of entomology* 18(1):47–72.

- Ciliberto, F., G. Moschini, and E.D. Perry. 2019. “Valuing product innovation: genetically engineered varieties in US corn and soybeans.” *The RAND Journal of Economics* 50(3):615–644.
- Cirruzzo, C., and A. Cancryn. 2025. “‘Nothing ... off limits’: Kennedy lays out plan for HHS.” *Politico*. Available at: <https://www.politico.com/news/2025/02/18/kennedy-lays-out-hhs-plan-00204675> [Accessed May 8, 2025].
- Claassen, R., M. Bowman, J. McFadden, D. Smith, and S. Wallander. 2018. “Tillage Intensity and Conservation Cropping in the United States.” No. EIB-197, U.S. Department of Agriculture, Economic Research Service.
- Clément, T., R. Joya, C. Bresson, and C. Clément. 2018. “Market developments and policy evaluation aspects of the plant protein sector in the EU.” European Commission. Available at: <https://data.europa.eu/doi/10.2762/022741> [Accessed April 21, 2025].
- Costinot, A., D. Donaldson, and C.B. Smith. 2014. “Evolving Comparative Advantage and the Impact of Climate Change in Agricultural Markets: Evidence from 1.7 Million Fields around the World.” NBER. Available at: <http://www.nber.org/papers/w20079>.
- Cutforth, H.W., S.M. McGinn, K.E. McPhee, and P.R. Miller. 2007. “Adaptation of Pulse Crops to the Changing Climate of the Northern Great Plains.” *Agronomy Journal* 99(6):1684–1699.
- Daba, S.D., and C.F. Morris. 2022. “Pea proteins: Variation, composition, genetics, and functional properties.” *Cereal Chemistry* 99(1):8–20.
- Danielson, E., and A. Watters. 2023. “Agricultural Biotechnology Annual.” No. CA2023-0047, USDA Foreign Agricultural Service. Available at: https://apps.fas.usda.gov/newgainapi/api/Report/DownloadReportByFileName?fileName=Agricultural%20Biotechnology%20Annual_Ottawa_Canada_CA2023-0047.pdf [Accessed May 28, 2025].
- Davis, K.E., S.C. Babu, and C. Ragasa. 2020. “Agricultural extension: Global status and performance in selected countries.” International Food Policy Research Institute. Available at: <https://hdl.handle.net/10568/139878> [Accessed October 18, 2024].
- Degani, E., S.G. Leigh, H.M. Barber, H.E. Jones, M. Lukac, P. Sutton, and S.G. Potts. 2019. “Crop rotations in a climate change scenario: short-term effects of crop diversity on resilience and ecosystem service provision under drought.” *Agriculture, Ecosystems & Environment* 285:106625.
- Devi, J., V. Sagar, G.P. Mishra, P.K. Jha, N. Gupta, R.K. Dubey, P.M. Singh, T.K. Behera, and P.V.V. Prasad. 2023. “Heat stress tolerance in peas (*Pisum sativum* L.): Current status and way forward.” *Frontiers in Plant Science* 13. Available at: <https://www.frontiersin.org/articles/10.3389/fpls.2022.1108276/full> [Accessed July 16, 2025].

- Dong, F., L. Dodson, R. Nemec Boehm, C. Douglass, M. Ranville, and R. Olver. 2024. “The relative importance of herbicide use for conservation tillage adoption by U.S. corn and soybean producers” D. Hui, ed. *PLOS ONE* 19(11):e0311960.
- Durand-Morat, A., and L.L. Nalley. 2019. “Economic Benefits of Controlling Red Rice: A Case Study of the United States.” *Agronomy* 9(8):422.
- Durand-Morat, A., L.L. Nalley, and G. Thoma. 2018. “The implications of red rice on food security.” *Global Food Security* 18(July):62–75.
- Eklund, P. 1983. “Technology development and adoption rates: Systems approach for agricultural research and extension.” *Food Policy* 8(2):141–153.
- Ellsbury, M.M., and R.E. Lee. 2004. “Supercooling and cold-hardiness in eggs of western and northern corn rootworms.” *Entomologia Experimentalis et Applicata* 111(3):159–163.
- Esposito, S., D. Carputo, T. Cardi, and P. Tripodi. 2019. “Applications and Trends of Machine Learning in Genomics and Phenomics for Next-Generation Breeding.” *Plants* 9(1):34.
- European Commission. 2010. *A decade of EU-funded GMO research (2001 - 2010)*. Luxembourg: European Union.
- Falck-Zepeda, J.B., G. Traxler, and R.G. Nelson. 2000. “Surplus Distribution from the Introduction of a Biotechnology Innovation.” *American Journal of Agricultural Economics* 82(2):360–369.
- FAO. 2023. “FAOSTAT database: Crops and livestock products.” Available at: <https://www.fao.org/faostat/en/#data/>.
- Feder, G., R.E. Just, and D. Zilberman. 1985. “Adoption of Agricultural Innovations in Developing Countries: A Survey.” *Economic Development and Cultural Change* 33(2):255–298.
- Fedoruk, L.K., E.N. Johnson, and S.J. Shirtliffe. 2011. “The Critical Period of Weed Control for Lentil in Western Canada.” *Weed Science* 59(4):517–526.
- Fernandez-Cornejo, J., S. Wechsler, M. Livingston, and L. Mitchell. 2014. “Genetically Engineered Crops in the United States.” U.S. Department of Agriculture, Economic Research Service. Available at: <http://www.ssrn.com/abstract=2503388>.
- Finger, R., A. Henningsen, J. Höhler, R. Huber, J. Rommel, and C. Grebitus. 2024. “Open Science in Agricultural Economics.” *Q Open*:q0ae029.
- Foster, A.D., and M.R. Rosenzweig. 1995. “Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture.” *Journal of Political Economy* 103(6):1176–1209.

- Foster, A.D., and M.R. Rosenzweig. 2010. "Microeconomics of Technology Adoption." *Annual Review of Economics* 2(1):395–424.
- Franck, W., C. Chen, S. Franck, Y.A. Mohammed, M.T. Abdelhamid, P. Miller, P.M. Carr, P. Lamb, J. Torrior, Q. Khan, and K. McVay. 2024. "Cultivar and environmental impacts on protein and mineral concentrations in peas (*Pisum sativum* L.)." *Crop Science* 64(1):287–302.
- Garrison, C. 2023. "Explainer: What is the US-Mexico GM corn dispute about?" *Reuters*. Available at: <https://www.reuters.com/markets/commodities/what-is-us-mexico-gm-corn-dispute-about-2023-03-08/> [Accessed May 8, 2025].
- Genius, M., P. Koundouri, C. Nauges, and V. Tzouvelekas. 2014. "Information Transmission in Irrigation Technology Adoption and Diffusion: Social Learning, Extension Services, and Spatial Effects." *American Journal of Agricultural Economics* 96(1):328–344.
- Godfray, H.C.J., J.R. Beddington, I.R. Crute, L. Haddad, D. Lawrence, J.F. Muir, J. Pretty, S. Robinson, S.M. Thomas, and C. Toulmin. 2010. "Food Security: The Challenge of Feeding 9 Billion People." *Science* 327(5967):812–818.
- Godfrey, L.D., L.J. Meinke, R.J. Wright, and G.L. Hein. 1995. "Environmental and Edaphic Effects on Western Corn Root worm (Coleoptera: Chrysomelidae) Overwintering Egg Survival." *Journal of Economic Entomology* 88(5):1445–1454.
- Green, J.M. 2012. "The benefits of herbicide-resistant crops." *Pest Management Science* 68(10):1323–1331.
- Griliches, Z. 1960. "Hybrid Corn and the Economics of Innovation." *Science* 132(3422):275–280.
- Guo, P., and K. Al-Khatib. 2003. "Temperature effects on germination and growth of redroot pigweed (*Amaranthus retroflexus*), Palmer amaranth (*A. palmeri*), and common waterhemp (*A. rudis*)." *Weed Science* 51(6):869–875.
- Gurian-Sherman, D. 2009. "Failure to yield: Evaluating the Performance of Genetically Engineered Crops." Union of Concerned Scientists.
- Hakim, D. 2016. "Doubts About the Promised Bounty of Genetically Modified Crops." *The New York Times*. Available at: <https://www.nytimes.com/2016/10/30/business/gmo-promise-falls-short.html>.
- Hansen, C.W., and A.M. Wingender. 2023. "National and Global Impacts of Genetically Modified Crops." *American Economic Review: Insights* 5(2):224–240.
- Heady, E.O. 1957. "An Econometric Investigation of the Technology of Agricultural Production Functions." *Econometrica* 25(2):249.

- Heikonen, S., M. Heino, M. Jalava, S. Siebert, D. Viviroli, and M. Kummu. 2025. "Climate change threatens crop diversity at low latitudes." *Nature Food*. Available at: <https://www.nature.com/articles/s43016-025-01135-w> [Accessed March 31, 2025].
- Helman, D., and D.J. Bonfil. 2022. "Six decades of warming and drought in the world's top wheat-producing countries offset the benefits of rising CO₂ to yield." *Scientific Reports* 12(1):7921.
- Herring, R., and R. Paarlberg. 2016. "The Political Economy of Biotechnology." *Annual Review of Resource Economics* 8:397–416.
- Hiu, S., T. Yong, J. Hasoon, M.D. Teare, J. Taylor, and N. Lin. 2024. "Instrumental variables in real-world clinical studies of dementia and neurodegenerative disease: Systematic review of the subject-matter argumentation, falsification test, and study design strategies to justify a valid instrument." *Brain and Behavior* 14(1):e3371.
- Howden, S.M., J.-F. Soussana, F.N. Tubiello, N. Chhetri, M. Dunlop, and H. Meinke. 2007. "Adapting agriculture to climate change." *Proceedings of the National Academy of Sciences* 104(50):19691–19696.
- Hsiang, S., Lobell, David, M. Roberts, and W. Schlenker. 2013. "Climate and Crop Yields in Australia, Brazil, China, Europe and the United States." *SSRN Electronic Journal*. Available at: <http://www.ssrn.com/abstract=2977571> [Accessed August 26, 2024].
- Hufford, M.B., J.C. Berny Mier y Teran, and P. Gepts. 2019. "Crop Biodiversity: An Unfinished Magnum Opus of Nature." *Annual Review of Plant Biology* 70(1):727–751.
- Hutchins, J.P., and S.H. Irwin. 2025. "Productivity Growth from Genetic Improvement: Evidence from Illinois Soybean Trial Data." *American Journal of Agricultural Economics*:ajae.12555.
- Hyman, G., H. Espinosa, P. Camargo, D. Abreu, M. Devare, E. Arnaud, C. Porter, L. Mwanzia, K. Sonder, and S. Traore. 2017. "Improving agricultural knowledge management: The AgTrials experience." *F1000Research* 6:317.
- Institute of Medicine and National Research Council. 2004. *Safety of Genetically Engineered Foods: Approaches to Assessing Unintended Health Effects*. Washington, DC: The National Academies Press. Available at: <https://nap.nationalacademies.org/catalog/10977/safety-of-genetically-engineered-foods-approaches-to-assessing-unintended-health>.
- Jägermeyr, J., C. Müller, A.C. Ruane, J. Elliott, J. Balkovic, O. Castillo, B. Faye, I. Foster, C. Folberth, J.A. Franke, K. Fuchs, J.R. Guarin, J. Heinke, G. Hoogenboom, T. Iizumi, A.K. Jain, D. Kelly, N. Khabarov, S. Lange, T.-S. Lin, W. Liu, O. Mialyk, S. Minoli, E.J. Moyer, M. Okada, M. Phillips, C. Porter, S.S. Rabin, C. Scheer, J.M. Schneider, J.F. Schyns, R. Skalsky, A. Smerald, T. Stella, H. Stephens, H. Webber, F. Zabel, and C. Rosenzweig. 2021. "Climate impacts on global agriculture emerge earlier in new generation of climate and crop models." *Nature Food* 2(11):873–885.

- Jaksons, R., K. Falkner, and E. Moltchanova. 2022. “Modelling the emergence dynamics of the western corn rootworm beetle (*Diabrotica virgifera virgifera*).” *Scientific Reports* 12(1):2340.
- Joshi, M., Y. Timilsena, and B. Adhikari. 2017. “Global production, processing and utilization of lentil: A review.” *Journal of Integrative Agriculture* 16(12):2898–2913.
- Joshi, P.K., and P.P. Rao. 2016. “Global and regional pulse economies: Current trends and outlook.” International Food Policy Research Institute.
- Just, D.R., S. Wolf, and D. Zilberman. 2003. “Principles of risk management service relations in agriculture.” *Agricultural Systems* 75(2–3):199–213.
- Kang, H., A. Zhang, T.T. Cai, and D.S. Small. 2016. “Instrumental Variables Estimation With Some Invalid Instruments and its Application to Mendelian Randomization.” *Journal of the American Statistical Association* 111(513):132–144.
- Kantor, S., and A. Whalley. 2019. “Research Proximity and Productivity: Long-Term Evidence from Agriculture.” *Journal of Political Economy* 127(2):819–854.
- Keane, M., and T. Neal. 2023. “Instrument strength in IV estimation and inference: A guide to theory and practice.” *Journal of Econometrics* 235(2):1625–1653.
- Khazaei, H., M. Subedi, M. Nickerson, C. Martínez-Villaluenga, J. Frias, and A. Vandenberg. 2019. “Seed Protein of Lentils: Current Status, Progress, and Food Applications.” *Foods* 8(9):391.
- Kleibergen, F., and R. Paap. 2006. “Generalized reduced rank tests using the singular value decomposition.” *Journal of Econometrics* 133(1):97–126.
- Klümper, W., and M. Qaim. 2014. “A Meta-Analysis of the Impacts of Genetically Modified Crops.” *PLoS ONE* 9(11).
- Knezevic, S.Z., S.P. Evans, E.E. Blankenship, R.C. Van Acker, and J.L. Lindquist. 2002. “Critical period for weed control: the concept and data analysis.” *Weed Science* 50(6):773–786.
- Knott, C.M., and H.M. Halila. 1988. “Weeds in food legumes: problems, effects and control.” In R. J. Summerfield, ed. *World crops: Cool season food legumes*. Current Plant Science and Biotechnology in Agriculture. Dordrecht: Springer Netherlands, pp. 535–548. Available at: http://link.springer.com/10.1007/978-94-009-2764-3_45 [Accessed June 12, 2025].
- Ko, M., and A.F. Ramsey. 2022. “Warming Temperatures and Potential Adaptation through Breeding: Evidence from U.S. Soft Winter Wheat.” In Agricultural & Applied Economics Association Annual Meeting. Anaheim, CA.

- Kouser, S., and M. Qaim. 2014. "Bt cotton, damage control and optimal levels of pesticide use in Pakistan." *Environment and Development Economics* 19(6):704–723.
- Krishnan, P., and M. Patnam. 2014. "Neighbors and Extension Agents in Ethiopia: Who Matters More for Technology Adoption?" *American Journal of Agricultural Economics* 96(1):308–327.
- Kropff, M.J., S.E. Weaver, and M.A. Smits. 1992. "Use of Ecophysiological Models for Crop-Weed Interference: Relations Amongst Weed Density, Relative Time of Weed Emergence, Relative Leaf Area, and Yield Loss." *Weed Science* 40(2):296–301.
- Krupinsky, J.M., K.L. Bailey, M.P. McMullen, B.D. Gossen, and T.K. Turkington. 2002. "Managing Plant Disease Risk in Diversified Cropping Systems." *Agronomy Journal* 94(2):198–209.
- Kukal, M.S., and S. Irmak. 2018. "Climate-Driven Crop Yield and Yield Variability and Climate Change Impacts on the U.S. Great Plains Agricultural Production." *Scientific Reports* 8(1):3450.
- Kumar, J., R.R. Mir, S. Shafi, D. Sen Gupta, I. Djaloovic, J. Miladinovic, Rahul Kumar, S. Kumar, and Rajeev Kumar. 2021. "Genomics Associated Interventions for Heat Stress Tolerance in Cool Season Adapted Grain Legumes." *International Journal of Molecular Sciences* 23(1):399.
- Kutcher, H.R., J.S. Warland, and S.A. Brandt. 2010. "Temperature and precipitation effects on canola yields in Saskatchewan, Canada." *Agricultural and Forest Meteorology* 150(2):161–165.
- Landau, C.A., A.G. Hager, and M.M. Williams. 2022. "Deteriorating weed control and variable weather portends greater soybean yield losses in the future." *Science of The Total Environment* 830:154764.
- Landau, C.A., A.G. Hager, and M.M. Williams. 2021. "Diminishing weed control exacerbates maize yield loss to adverse weather." *Global Change Biology* 27(23):6156–6165.
- Lee, S., Y. Ji, and G. Moschini. 2022. "Agricultural innovation and adaptation to climate change: Insights from US maize." *Journal of the Agricultural and Applied Economics Association* 1(2):165–179.
- Lee, S., and G. Moschini. 2022. "On the value of innovation and extension information: SCN-resistant soybean varieties." *American Journal of Agricultural Economics* 104(4):1177–1202.
- Leonelli, S., R.P. Davey, E. Arnaud, G. Parry, and R. Bastow. 2017. "Data management and best practice for plant science." *Nature Plants* 3(6):17086.
- Lesk, C., P. Rowhani, and N. Ramankutty. 2016. "Influence of extreme weather disasters on global crop production." *Nature* 529(7584):84–87.

- Lichtenberg, E. 1989. "Land Quality, Irrigation Development, and Cropping Patterns in the Northern High Plains." *American Journal of Agricultural Economics* 71(1):187–194.
- Lobell, D.B., M. Bänziger, C. Magorokosho, and B. Vivek. 2011. "Nonlinear heat effects on African maize as evidenced by historical yield trials." *Nature Climate Change* 1:42–45.
- Lobell, D.B., M.B. Burke, C. Tebaldi, M.D. Mastrandrea, W.P. Falcon, and R.L. Naylor. 2008. "Prioritizing climate change adaptation needs for food security in 2030." *Science* 319:607–610.
- Lupwayi, N.Z., and A.C. Kennedy. 2007. "Grain Legumes in Northern Great Plains: Impacts on Selected Biological Soil Processes." *Agronomy Journal* 99(6):1700–1709.
- Lusk, J.L., J. Tack, and N.P. Hendricks. 2017. "Heterogeneous Yield Impacts From Adoption of Genetically Engineered Corn and the Importance of Controlling for Weather." National Bureau of Economic Research. Available at: <http://www.nber.org/papers/w23519>.
- MacDonald, J.M., X. Dong, and K.O. Fuglie. 2023. "Concentration and competition in U.S. agribusiness." No. EIB-256, U.S. Department of Agriculture, Economic Research Service. Available at: <https://handle.nal.usda.gov/10113/8054022> [Accessed May 9, 2025].
- Maertens, A., H. Michelson, and V. Nourani. 2021. "How Do Farmers Learn from Extension Services? Evidence from Malawi." *American Journal of Agricultural Economics* 103(2):569–595.
- Mallory-Smith, C.A., and E. Sanchez Olguin. 2011. "Gene Flow from Herbicide-Resistant Crops: It's Not Just for Transgenes." *Journal of Agricultural and Food Chemistry* 59(11):5813–5818.
- Manners, R., C. Varela-Ortega, and J. Van Etten. 2020. "Protein-rich legume and pseudo-cereal crop suitability under present and future European climates." *European Journal of Agronomy* 113:125974.
- Mapfumo, E., D.S. Chanasyk, D. Puurveen, S. Elton, and S. Acharya. 2023. "Historic climate change trends and impacts on crop yields in key agricultural areas of the prairie provinces in Canada: a literature review." *Canadian Journal of Plant Science* 103(3):243–258.
- McDonald, G.K., K.L. Hollaway, and L. McMurray. 2007. "Increasing plant density improves weed competition in lentil (*Lens culinaris*)." *Australian Journal of Experimental Agriculture* 47(1):48.
- McFarland, B.A., N. AlKhalifah, M. Bohn, J. Bubert, E.S. Buckler, I. Ciampitti, J. Edwards, D. Ertl, J.L. Gage, C.M. Falcon, S. Flint-Garcia, M.A. Gore, C. Graham, C.N. Hirsch, J.B. Holland, E. Hood, D. Hooker, D. Jarquin, S.M. Kaeppler, J. Knoll, G. Kruger, N. Lauter, E.C. Lee, D.C. Lima, A. Lorenz, J.P. Lynch, J. McKay, N.D. Miller, S.P. Moose, S.C. Murray, R. Nelson, C. Poudyal, T. Rocheford, O. Rodriguez, M.C. Romy, J.C. Schnable, P.S. Schnable, B. Scully, R. Sekhon, K. Silverstein, M. Singh, M. Smith, E.P.

- Spalding, N. Springer, K. Thelen, P. Thomison, M. Tuinstra, J. Wallace, R. Walls, D. Wills, R.J. Wissler, W. Xu, C.-T. Yeh, and N. De Leon. 2020. “Maize genomes to fields (G2F): 2014–2017 field seasons: genotype, phenotype, climatic, soil, and inbred ear image datasets.” *BMC Research Notes* 13(1):71.
- Miller, N., J. Tack, and J. Bergtold. 2021. “The Impacts of Warming Temperatures on US Sorghum Yields and the Potential for Adaptation.” *American Journal of Agricultural Economics* 103(5):1742–1758.
- Miller, P.R., B.G. McConkey, G.W. Clayton, S.A. Brandt, J.A. Staricka, A.M. Johnston, G.P. Lafond, B.G. Schatz, D.D. Baltensperger, and K.E. Neill. 2002. “Pulse Crop Adaptation in the Northern Great Plains.” *Agronomy Journal* 94(2):261–272.
- Mohammed, Y.A., C. Chen, M.K. Walia, J.A. Torrión, K. McVay, P. Lamb, P. Miller, J. Eckhoff, J. Miller, and Q. Khan. 2018. “Dry pea (*Pisum sativum* L.) protein, starch, and ash concentrations as affected by cultivar and environment” C. Willenborg, ed. *Canadian Journal of Plant Science* 98(5):1188–1198.
- Morgounov, A., K. Sonder, A. Abugalieva, V. Bhadauria, R.D. Cuthbert, V. Shamanin, Y. Zelenskiy, and R.M. DePauw. 2018. “Effect of climate change on spring wheat yields in North America and Eurasia in 1981-2015 and implications for breeding” A. Zhang, ed. *PLOS ONE* 13(10):e0204932.
- Muehlbauer, F.J., S. Cho, A. Sarker, K.E. McPhee, C.J. Coyne, P.N. Rajesh, and R. Ford. 2006. “Application of biotechnology in breeding lentil for resistance to biotic and abiotic stress.” *Euphytica* 147(1–2):149–165.
- Mulimbi, W., L.L. Nalley, J. Strauss, and K. Ala-Kokko. 2023. “Economic and environmental comparison of conventional and conservation agriculture in South African wheat production.” *Agrekon* 62(2):133–151.
- Murray, M.P. 2006. “Avoiding Invalid Instruments and Coping with Weak Instruments.” *Journal of Economic Perspectives* 20(4):111–132.
- Mutuc, M.E., R.M. Rejesus, and J.M. Yorobe. 2011. “Yields, Insecticide Productivity, and Bt Corn: Evidence from Damage Abatement Models in the Philippines.” *AgBioForum* 14(2):35–46.
- Nalley, L., J. Tack, A. Barkley, K. Jagadish, and K. Brye. 2016. “Quantifying the agronomic and economic performance of hybrid and conventional rice varieties.” *Agronomy Journal* 108(4):1514–1523.
- Nalley, L.L., A. Barkley, B. Watkins, and J. Hignight. 2009. “Enhancing Farm Profitability through Portfolio Analysis: The Case of Spatial Rice Variety Selection.” *Journal of Agricultural and Applied Economics* 41(3):641–652.
- National Academies of Sciences Engineering and Medicine. 2016. *Genetically Engineered Crops: Experiences and Prospects*. Washington, DC: National Academies Press.

- National Research Council. 2010. *Impact of Genetically Engineered Crops on Farm Sustainability in the United States*. Washington, D.C.: National Academies Press. Available at: <http://www.nap.edu/catalog/12804>.
- Nerlove, M. 1979. "The Dynamics of Supply: Retrospect and Prospect." *American Journal of Agricultural Economics* 61(5):874–888.
- Ney, B., and O. Turc. 1993. "Heat-Unit-Based Description of the Reproductive Development of Pea." *Crop Science* 33(3):510–514.
- Nolan, E., and P. Santos. 2012. "The contribution of genetic modification to changes in corn yield in the United States." *American Journal of Agricultural Economics* 94(5):1171–1188.
- Oerke, E.-C. 2006. "Crop losses to pests." *The Journal of Agricultural Science* 144(1):31–43.
- Olmstead, A.L., and P.W. Rhode. 2011. "Adapting North American wheat production to climatic challenges, 1839–2009." *Proceedings of the National Academy of Sciences* 108(2):480–485.
- Ortiz-Bobea, A., T.R. Ault, C.M. Carrillo, R.G. Chambers, and D.B. Lobell. 2021. "Anthropogenic climate change has slowed global agricultural productivity growth." *Nature Climate Change* 11(4):306–312.
- Ortiz-Bobea, A., R.G. Chambers, Y. He, and D.B. Lobell. 2025. "Large increases in public R&D investment are needed to avoid declines of US agricultural productivity." *Proceedings of the National Academy of Sciences* 122(11):e2411010122.
- Panescu, P., M. Carter, M. Cohen, D. Gertner, E. Ignaszewski, S. Murray, M. O'Donnell, B. Pierce, and S. Voss. 2023. "2022 State of the Industry Report: Plant-based meat, seafood, eggs and dairy." Good Food Institute. Available at: <https://gfi.org/resource/plant-based-meat-eggs-and-dairy-state-of-the-industry-report/>.
- Pardey, P.G., and J.M. Alston. 2021. "Unpacking the Agricultural Black Box: The Rise and Fall of American Farm Productivity Growth." *The Journal of Economic History* 81(1):114–155.
- Patterson, D.T. 1995. "Effects of Environmental Stress on Weed/Crop Interactions." *Weed Science* 43(3):483–490.
- Pearson, C.H., and A. Atucha. 2015. "Agricultural Experiment Stations and Branch Stations in the United States." *Natural Sciences Education* 44(1):1–5.
- Perry, E.D., D.A. Hennessy, and G.C. Moschini. 2022. "Uncertainty and learning in a technologically dynamic industry: Seed density in U.S. maize." *American Journal of Agricultural Economics* 104(4):1388–1410.

- Perry, E.D., G. Moschini, and D.A. Hennessy. 2016. "Testing for Complementarity: Glyphosate Tolerant Soybeans and Conservation Tillage." *American Journal of Agricultural Economics* 98(3):765–784.
- PRISM Climate Group. 2023. "PRISM Gridded Climate Data." Available at: <https://prism.oregonstate.edu>.
- Qaim, M. 2003. "Bt cotton in India: Field trial results and economic projections." *World Development* 31(12):2115–2127.
- Qaim, M. 2009. "The Economics of Genetically Modified Crops." *Annual Review of Resource Economics* 1(1):665–694.
- Qian, B., Q. Jing, G. Bélanger, J. Shang, T. Huffman, J. Liu, and G. Hoogenboom. 2018. "Simulated Canola Yield Responses to Climate Change and Adaptation in Canada." *Agronomy Journal* 110(1):133–146.
- Qian, B., X. Zhang, W. Smith, B. Grant, Q. Jing, A.J. Cannon, D. Neilsen, B. McConkey, G. Li, B. Bonsal, H. Wan, L. Xue, and J. Zhao. 2019. "Climate change impacts on Canadian yields of spring wheat, canola and maize for global warming levels of 1.5 °C, 2.0 °C, 2.5 °C and 3.0 °C." *Environmental Research Letters* 14(7):074005.
- Ray, D.K., N.D. Mueller, P.C. West, and J.A. Foley. 2013. "Yield Trends Are Insufficient to Double Global Crop Production by 2050" J. P. Hart, ed. *PLoS ONE* 8(6):e66428.
- Ray, D.K., P.C. West, M. Clark, J.S. Gerber, A.V. Prishchepov, and S. Chatterjee. 2019. "Climate change has likely already affected global food production" Y. H. Jung, ed. *PLOS ONE* 14(5):e0217148.
- Reynolds, M.P., H.J. Braun, A.J. Cavalieri, S. Chapotin, W.J. Davies, P. Ellul, C. Feuillet, B. Govaerts, M.J. Kropff, H. Lucas, J. Nelson, W. Powell, E. Quilligan, M.W. Rosegrant, R.P. Singh, K. Sonder, H. Tang, S. Visscher, and R. Wang. 2017. "Improving global integration of crop research." *Science* 357(6349):359–360.
- Reynolds, M.P., J. Hellin, B. Govaerts, P. Kosina, K. Sonder, P. Hobbs, and H. Braun. 2012. "Global crop improvement networks to bridge technology gaps." *Journal of Experimental Botany* 63(1):1–12.
- Roberts, E.H., R.J. Summerfield, R.H. Ellis, and K.A. Stewart. 1988. "Photothermal Time for Flowering in Lentils (*Lens culinaris*) and the Analysis of Potential Vernalization Responses." *Annals of Botany* 61(1):29–39.
- Robertson, S.M., S.R. Jeffrey, J.R. Unterschultz, and P.C. Boxall. 2013. "Estimating yield response to temperature and identifying critical temperatures for annual crops in the Canadian prairie region." *Canadian Journal of Plant Science* 93(6):1237–1247.

- Rosenzweig, C., A. Iglesias, X. Yang, P. Epstein, and E. Chivian. 2001. "Climate Change and Extreme Weather Events; Implications for Food Production, Plant Diseases, and Pests." *Global Change & Human Health* 2:90–104.
- Rosenzweig, C., and M.L. Parry. 1994. "Potential impact of climate change on world food supply." *Nature* 367(6459):133–138.
- Sanglestsawai, S., R.M. Rejesus, and J.M. Yorobe. 2014. "Do lower yielding farmers benefit from Bt corn? Evidence from instrumental variable quantile regressions." *Food Policy* 44:285–296.
- Sarangi, D., S. Irmak, J.L. Lindquist, S.Z. Knezevic, and A.J. Jhala. 2016. "Effect of Water Stress on the Growth and Fecundity of Common Waterhemp (*Amaranthus rudis*)." *Weed Science* 64(1):42–52.
- Saskatchewan Pulse Growers. 2023. "Staging Pulses for Herbicide Applications In-Crop." Available at: <https://saskpulse.com/resources/staging-pulses-for-herbicide-applications-in-crop/> [Accessed May 15, 2025].
- Scheitrum, D., K.A. Schaefer, and K. Nes. 2020. "Realized and potential global production effects from genetic engineering." *Food Policy* 93:101882.
- Schlenker, W., and M.J. Roberts. 2009. "Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change." *Proceedings of the National Academy of Sciences* 106(37):15594–15598.
- Shankar, B., R. Bennett, and S. Morse. 2008. "Production risk, pesticide use and GM crop technology in South Africa." *Applied Economics* 40(19):2489–2500.
- Shankar, B., and C. Thirtle. 2005. "Pesticide Productivity and Transgenic Cotton Technology: The South African Smallholder Case." *Journal of Agricultural Economics* 56(1):97–116.
- Shew, A.M., J.B. Tack, L.L. Nalley, P. Chaminuka, and S. Maali. 2021. "Yield gains larger in GM maize for human consumption than livestock feed in South Africa." *Nature Food* 2(2):104–109.
- Siddique, K.H.M., C. Johansen, N.C. Turner, M.-H. Jeuffroy, A. Hashem, D. Sakar, Y. Gan, and S.S. Alghamdi. 2012. "Innovations in agronomy for food legumes. A review." *Agronomy for Sustainable Development* 32(1):45–64.
- Sita, K., A. Sehgal, B. HanumanthaRao, R.M. Nair, P.V. Vara Prasad, S. Kumar, P.M. Gaur, M. Farooq, K.H.M. Siddique, R.K. Varshney, and H. Nayyar. 2017. "Food Legumes and Rising Temperatures: Effects, Adaptive Functional Mechanisms Specific to Reproductive Growth Stage and Strategies to Improve Heat Tolerance." *Frontiers in Plant Science* 8. Available at: <http://journal.frontiersin.org/article/10.3389/fpls.2017.01658/full> [Accessed July 16, 2025].

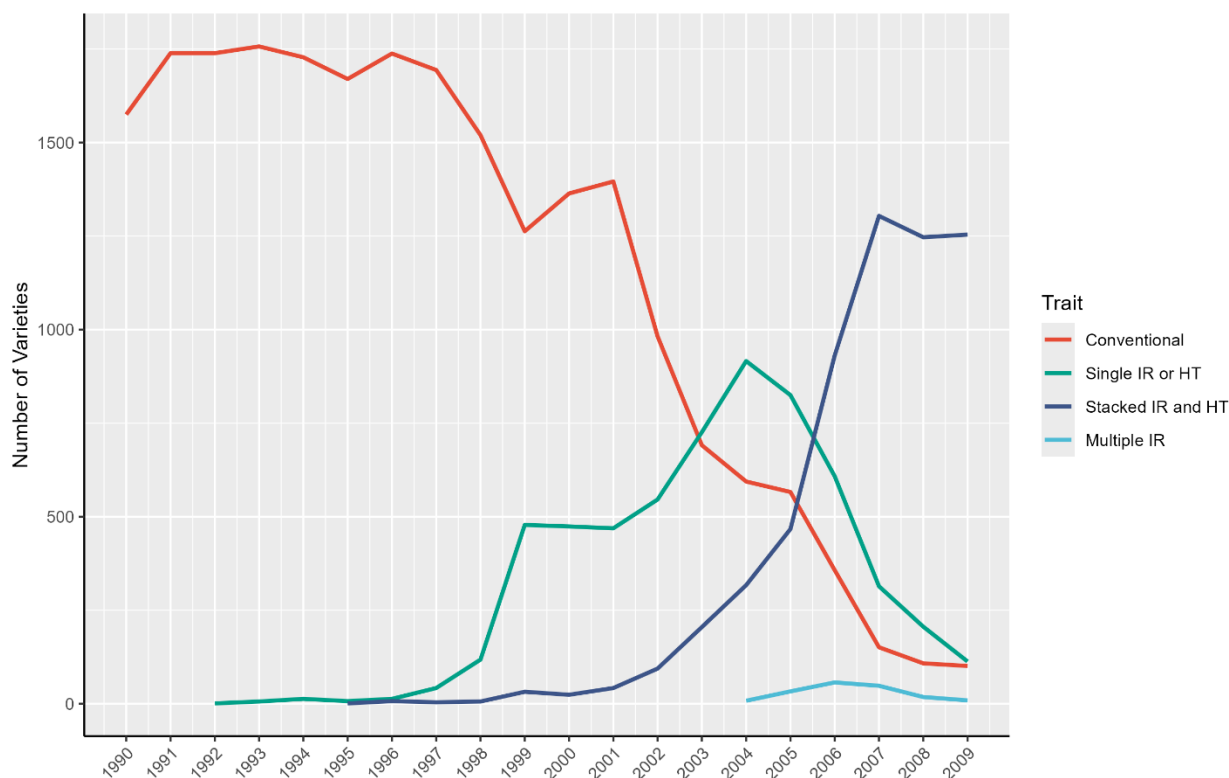
- Smit, B., and M.W. Skinner. 2002. "Adaptation options in agriculture to climate change: a typology." *Mitigation and Adaptation Strategies for Global Change* 7(1):85–114.
- Smitchger, J.A., I.C. Burke, and J.P. Yenish. 2012. "The Critical Period of Weed Control in Lentil (*Lens culinaris*) in the Pacific Northwest." *Weed Science* 60(1):81–85.
- Smyth, S.J. 2017. "Genetically modified crops, regulatory delays, and international trade." *Food and Energy Security* 6(2):78–86.
- Smyth, S.J., W.A. Kerr, and P.W.B. Phillips. 2015. "Global economic, environmental and health benefits from GM crop adoption." *Global Food Security* 7:24–29.
- Soltani, N., J.A. Dille, I.C. Burke, W.J. Everman, M.J. VanGessel, V.M. Davis, and P.H. Sikkema. 2017. "Perspectives on Potential Soybean Yield Losses from Weeds in North America." *Weed Technology* 31(1):148–154.
- Statistics Canada. 2025. "Table 32-10-0359-01 Estimated areas, yield, production, average farm price and total farm value of principal field crops, in metric and imperial units." Available at: <https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=3210035901> [Accessed June 10, 2025].
- Sunding, D., and D. Zilberman. 2001. "Chapter 4 The agricultural innovation process: Research and technology adoption in a changing agricultural sector." In pp. 207–261. Available at: <https://linkinghub.elsevier.com/retrieve/pii/S1574007201100071>.
- Tack, J., A. Barkley, and L.L. Nalley. 2015. "Effect of warming temperatures on US wheat yields." *Proceedings of the National Academy of Sciences* 112(22):6931–6936.
- Tack, J., A. Barkley, and L.L. Nalley. 2014. "Heterogeneous effects of warming and drought on selected wheat variety yields." *Climatic Change* 125(3–4):489–500.
- Tack, J., A. Barkley, T.W. Rife, J.A. Poland, and L.L. Nalley. 2016. "Quantifying variety-specific heat resistance and the potential for adaptation to climate change." *Global Change Biology* 22(8):2904–2912.
- Tack, J., J. Lingenfelser, and S.V.K. Jagadish. 2017. "Disaggregating sorghum yield reductions under warming scenarios exposes narrow genetic diversity in US breeding programs." *Proceedings of the National Academy of Sciences* 114(35):9296–9301.
- Tamburini, G., R. Bommarco, T.C. Wanger, C. Kremen, M.G.A. Van Der Heijden, M. Liebman, and S. Hallin. 2020. "Agricultural diversification promotes multiple ecosystem services without compromising yield." *Science Advances* 6(45):eaba1715.
- Tan, S., R.R. Evans, M.L. Dahmer, B.K. Singh, and D.L. Shaner. 2005. "Imidazolinone-tolerant crops: history, current status and future." *Pest Management Science* 61(3):246–257.

- Tao, A., R.K. Afshar, J. Huang, Y.A. Mohammed, M. Espe, and C. Chen. 2017. "Variation in Yield, Starch, and Protein of Dry Pea Grown Across Montana." *Agronomy Journal* 109(4):1491–1501.
- Tardieu, F., L. Cabrera-Bosquet, T. Pridmore, and M. Bennett. 2017. "Plant Phenomics, From Sensors to Knowledge." *Current Biology* 27(15):R770–R783.
- Thornton, M.M., R. Shrestha, Y. Wei, P.E. Thornton, S.-C. Kao, and B.E. Wilson. 2022. "Daymet: Daily Surface Weather Data on a 1-km Grid for North America, Version 4 R1." Available at: https://daac.ornl.gov/cgi-bin/dsvviewer.pl?ds_id=1219.
- Toepfer, S., and Ulrich Kuhlmann. 2005. "Natural Mortality Factors Acting on Western Corn Rootworm Populations: a Comparison between the United States and Central Europe." In S. Vidal, U. Kuhlmann, and C. R. Edwards, eds. London, UK: CAB International. Available at: <https://cabidigitallibrary.org>.
- Tolhurst, T.N., and A. Ker. 2025. "Warmer temperatures provide little benefit in offsetting cold stress in Canadian crop yields." *Environmental Research Letters*. Available at: <https://iopscience.iop.org/article/10.1088/1748-9326/adc9c9> [Accessed April 17, 2025].
- Train, K. 2009. "Chapter 2 Properties of Discrete Choice Models." In *Discrete Choice Methods with Simulation*. New York: Cambridge University Press.
- Trnka, M., F. Muška, D. Semerádová, M. Dubrovský, E. Kocmánková, and Z. Žalud. 2007. "European Corn Borer life stage model: Regional estimates of pest development and spatial distribution under present and future climate." *Ecological Modelling* 207(2–4):61–84.
- Troya, M., H. Kurawadwala, B. Byrne, R. Dowdy, and Z. Weston. 2022. "Plant-based meat: Anticipating 2030 production requirements." Good Food Institute.
- USDA ERS. 2025. "Adoption of Genetically Engineered Crops in the U.S." Available at: <https://www.ers.usda.gov/data-products/adoption-of-genetically-engineered-crops-in-the-u-s/>.
- USDA NASS. 2023. "Quick Stats." Available at: <https://quickstats.nass.usda.gov/>.
- USDA NASS. 2025. "Quick Stats." Available at: <https://quickstats.nass.usda.gov/> [Accessed June 11, 2025].
- Vermeulen, S.J., B.M. Campbell, and J.S.I. Ingram. 2012. "Climate Change and Food Systems." *Annual Review of Environment and Resources* 37(1):195–222.
- Wadman, M. 2024. "Pediatrics academy faces pushback on GMO advice." *Science* 385(6715):1260–1261.
- Wall, D.A., and P.M. McMullan. 1994. "Effectiveness of several new selective herbicides in lentils (*Lens culinaris*)." *Crop Protection* 13(7):553–557.

- Walter, S., J. Zehring, K. Mink, U. Quendt, K. Zocher, and S. Rohn. 2022. "Protein content of peas (*Pisum sativum*) and beans (*Vicia faba*)—Influence of cultivation conditions." *Journal of Food Composition and Analysis* 105:104257.
- Warne, T., S. Ahmed, C. Byker Shanks, and P. Miller. 2019. "Sustainability Dimensions of a North American Lentil System in a Changing World." *Frontiers in Sustainable Food Systems* 3(October). Available at: <https://www.frontiersin.org/article/10.3389/fsufs.2019.00088/full>.
- Wienhold, B.J., M.F. Vigil, J.R. Hendrickson, and J.D. Derner. 2018. "Vulnerability of crops and croplands in the US Northern Plains to predicted climate change." *Climatic Change* 146(1–2):219–230.
- Wolf, S., D. Just, and D. Zilberman. 2001. "Between data and decisions: the organization of agricultural economic information systems." *Research Policy* 30(1):121–141.
- World Health Organization. 2014. "Frequently asked questions on genetically modified foods." Available at: https://www.who.int/foodsafety/areas_work/food-technology/faq-genetically-modified-food/en/ [Accessed May 8, 2025].
- Xu, Z., D.A. Hennessy, K. Sardana, and G. Moschini. 2013. "The Realized Yield Effect of Genetically Engineered Crops: U.S. Maize and Soybean." *Crop Science* 53(3):735–745.
- Yang, Y., D. Tilman, Z. Jin, P. Smith, C.B. Barrett, Y.-G. Zhu, J. Burney, P. D'Odorico, P. Fantke, J. Fargione, J.C. Finlay, M.C. Rulli, L. Sloat, K. Jan Van Groenigen, P.C. West, L. Ziska, A.M. Michalak, the Clim-Ag Team, D.B. Lobell, M. Clark, J. Colquhoun, T. Garg, K.A. Garrett, C. Geels, R.R. Hernandez, M. Herrero, W.D. Hutchison, M. Jain, J.M. Jungers, B. Liu, N.D. Mueller, A. Ortiz-Bobea, J. Schewe, J. Song, J. Verheyen, P. Vitousek, Y. Wada, L. Xia, X. Zhang, and M. Zhuang. 2024. "Climate change exacerbates the environmental impacts of agriculture." *Science* 385(6713):eadn3747.
- Yenish, J.P., J. Brand, M. Pala, and A. Haddad. 2009. "Weed Management." In W. Erskine, F. Muehlbauer, A. Sarker, and B. Sharma, eds. *The lentil: botany, production and uses*. Wallingford UK: CABI, pp. 326–342.
- Yue, Y., P. Zhang, and Y. Shang. 2019. "The potential global distribution and dynamics of wheat under multiple climate change scenarios." *Science of The Total Environment* 688:1308–1318.
- Zabel, F., B. Putzenlechner, and W. Mauser. 2014. "Global Agricultural Land Resources – A High Resolution Suitability Evaluation and Its Perspectives until 2100 under Climate Change Conditions" J. P. Kropp, ed. *PLoS ONE* 9(9):e107522.
- Zentner, R.P., D.D. Wall, C.N. Nagy, E.G. Smith, D.L. Young, P.R. Miller, C.A. Campbell, B.G. McConkey, S.A. Brandt, G.P. Lafond, A.M. Johnston, and D.A. Derksen. 2002. "Economics of Crop Diversification and Soil Tillage Opportunities in the Canadian Prairies." *Agronomy Journal* 94(2):216–230.

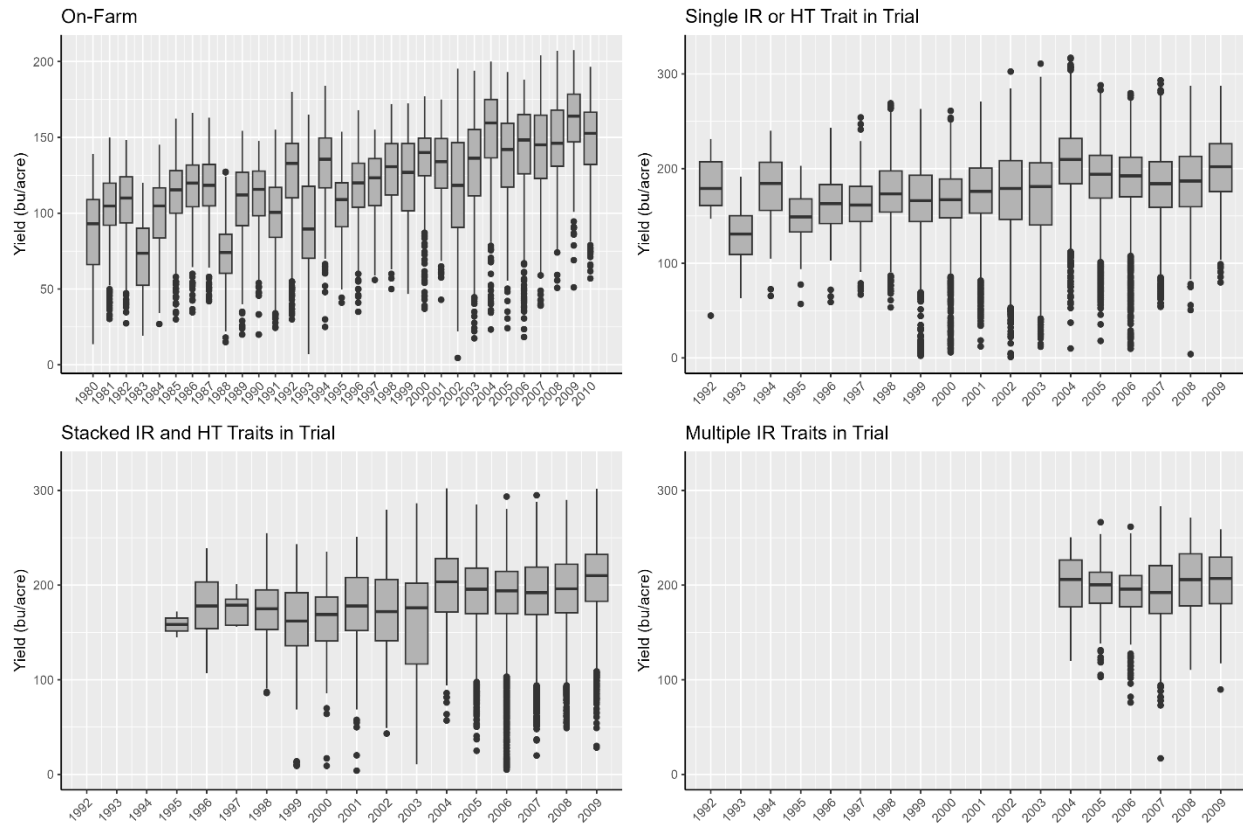
Appendix A - From Field Trials to Farm Adoption: Identifying the Productivity Effect of On-Farm Technology Adoption

Appendix Figure A.1. Number of corn varieties in trial data by trait: 1990-2009.



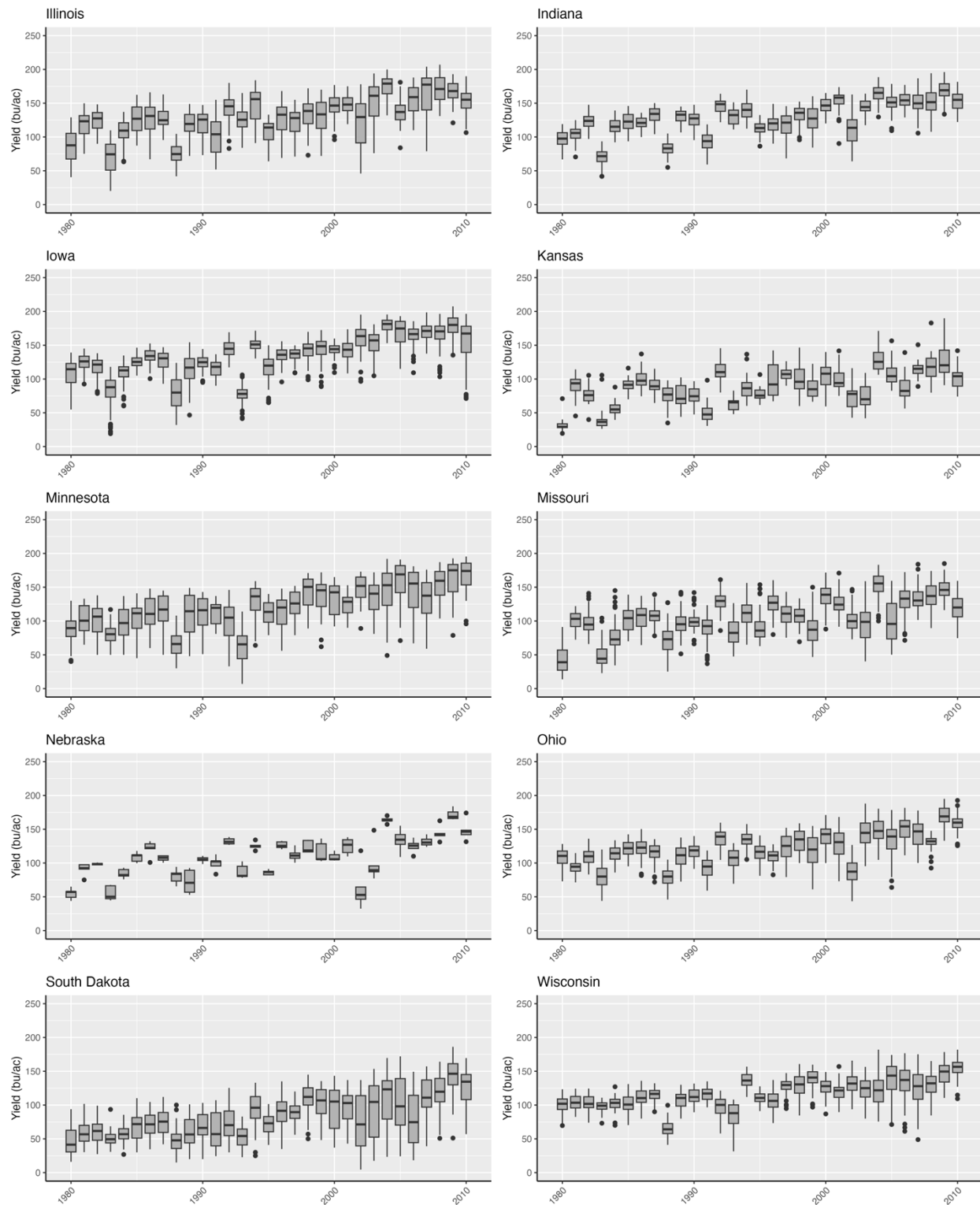
Notes: Variety trial data was obtained from annual field trial reports published by university extension services. IR and HT refer to insect resistant and herbicide tolerant traits, respectively. GM varieties became commercially available in 1996—several years after entering the trials in 1992. By 2009, conventional varieties have largely disappeared from the trials.

Appendix Figure A.2. Spatial and temporal variation of corn yields on-farm (1980-2010) and in-trial by each trait category (1992-2009).



Notes: County yield was calculated from production and area harvested data obtained from USDA NASS (2023) and trial yield was obtained from Nolan and Santos (2012). On-farm data varies at the county-year level and trial data varies at the variety-location-year level.

Appendix Figure A.3. In-sample spatial and temporal variation of on-farm corn yield by state: 1980-2010.



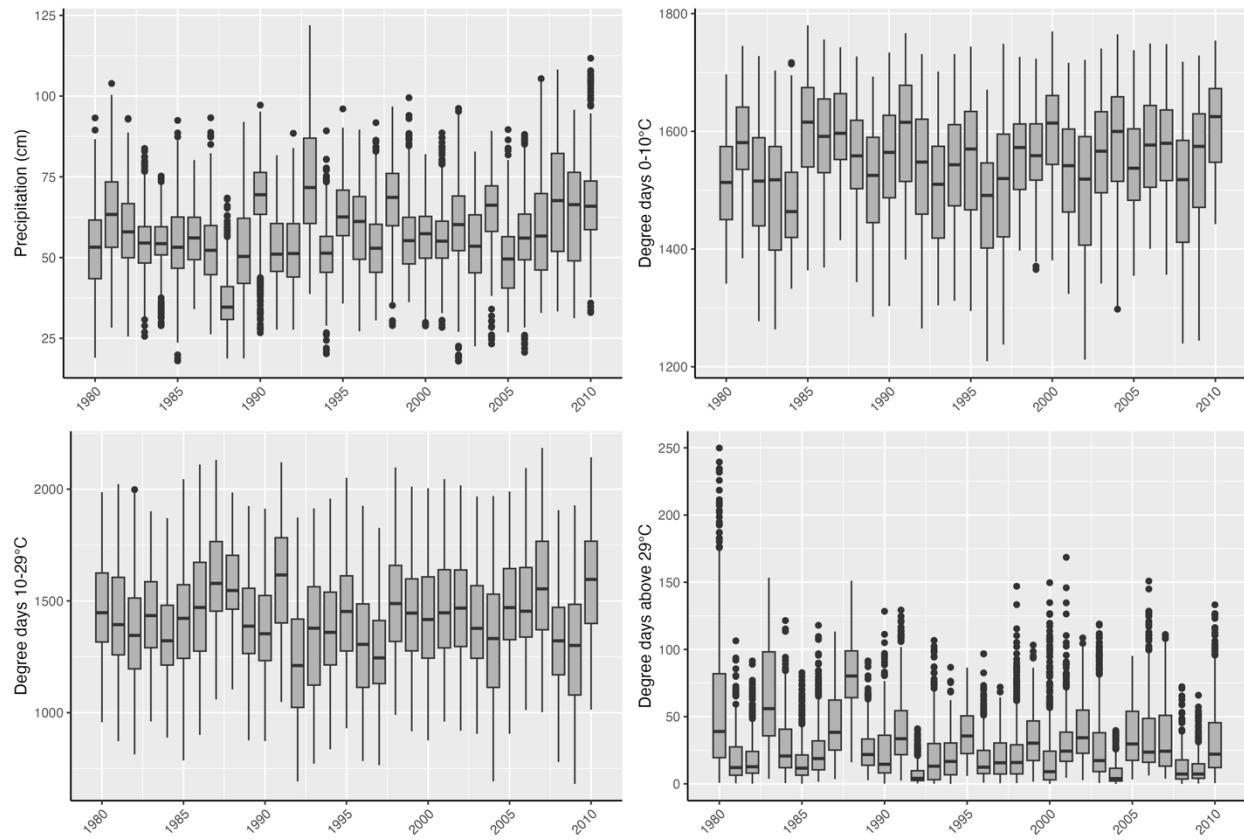
Notes: County-level yield was calculated from production and area harvested data obtained from USDA NASS, and boxplots were constructed for each year.

Appendix Table A.1. In-sample state-level GM corn adoption rates: 1996-2010.

Year	Iowa	Illinois	Indiana	Kansas	Minnesota	Missouri	Nebraska	Ohio	South Dakota	Wisconsin
1996	0.10	0.06	0.05	0.10	0.12	0.09	0.10	0.03	0.15	0.07
1997	0.13	0.07	0.07	0.13	0.16	0.11	0.13	0.04	0.20	0.09
1998	0.16	0.10	0.09	0.17	0.19	0.14	0.17	0.06	0.25	0.11
1999	0.20	0.12	0.11	0.21	0.24	0.17	0.22	0.07	0.32	0.14
2000	0.30	0.17	0.11	0.33	0.37	0.28	0.34	0.09	0.48	0.18
2001	0.32	0.16	0.12	0.38	0.36	0.32	0.34	0.11	0.47	0.18
2002	0.41	0.22	0.13	0.43	0.44	0.34	0.46	0.09	0.66	0.26
2003	0.45	0.28	0.16	0.47	0.53	0.42	0.52	0.09	0.75	0.32
2004	0.54	0.33	0.21	0.54	0.63	0.49	0.60	0.13	0.79	0.38
2005	0.60	0.36	0.26	0.63	0.66	0.55	0.69	0.18	0.83	0.46
2006	0.64	0.55	0.40	0.68	0.73	0.59	0.76	0.26	0.86	0.50
2007	0.78	0.74	0.59	0.82	0.86	0.62	0.79	0.41	0.93	0.64
2008	0.84	0.80	0.78	0.90	0.88	0.70	0.86	0.66	0.95	0.75
2009	0.86	0.84	0.79	0.91	0.88	0.77	0.91	0.67	0.96	0.77
2010	0.90	0.82	0.83	0.90	0.92	0.79	0.91	0.71	0.95	0.80

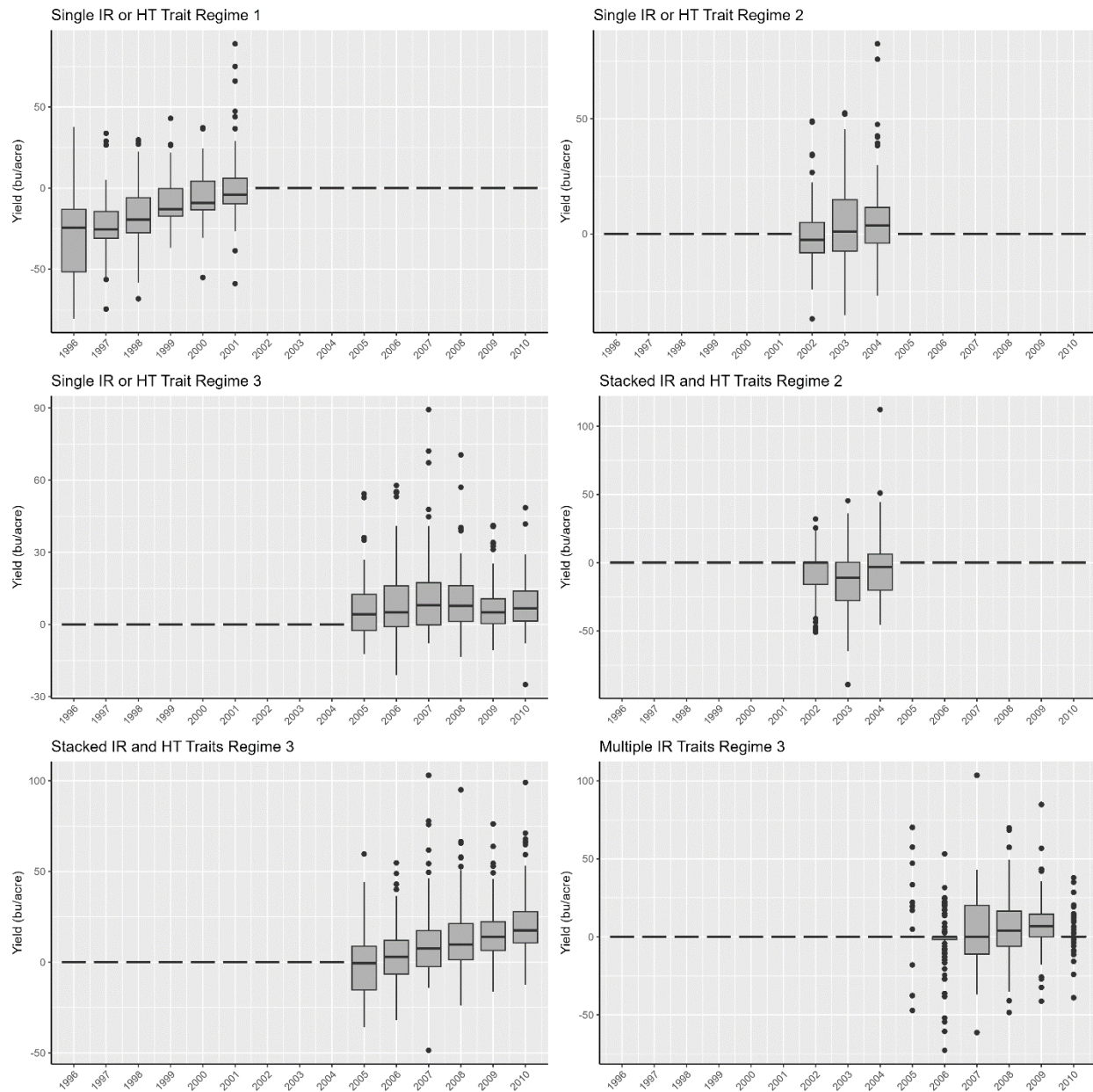
Notes: Adoption rates from 2000-2010 were obtained from USDA ERS and rates from 1996-1999 were interpolated. Interpolation procedure is described in more detail in text.

Appendix Figure A.4. Spatial and temporal variation of weather variables: 1980-2010.



Note: Weather data was obtained from PRISM. Degree day bins were calculated from interpolation between minimum and maximum temperatures. Weather variables were observed at the county-level and boxplots were constructed for each year.

Appendix Figure A.5. Cumulative maximum corn yield in trials by technology and regime: 1996-2010.



Notes: Cumulative maximum yield variables were observed at the county-level and boxplots were constructed for each year.

Appendix Table A.2. Data driven IV selection results obtained from sisVIVE.

Estimates of λ	Estimates of GM Effect	Number of Invalid IVs	Invalid IVs
39.22	19.56	0	
36.72	19.65	1	7
35.86	19.67	2	2,7
34.60	19.68	3	1,2,7
28.98	20.03	4	1,2,5,7
24.72	20.34	5	1,2,5,7,8
12.06	26.28	6	1,2,5,7,8,9
0.42	30.88	7	1,2,5,6,7,8,9
0.00	31.01	8	1,2,4,5,6,7,8,9

Notes: Estimated using the R package sisVIVE. Optimal $\lambda=24.72$. In the final column, the numbers correspond to the following instruments: 1= Single cumulative max yield R1 (b/a), 2= Single cumulative max yield R2 (b/a), 3= Single cumulative max yield R3 (b/a), 4= Stacked cumulative max yield R2 (b/a), 5= Stacked cumulative max yield R3 (b/a), 6= Multiple cumulative max yield R3 (b/a), 7= Single years in trial R1, 8= Stacked years in trial R2, 9= Multiple years in trial R3.

Appendix B - Effects of Warming on Cool-Season Pulse Varieties in North America

Appendix Table B.1. In-sample field pea trial location characteristics.

Location	Coordinates	Number of Years	Min Year	Max Year	Number of Cultivars	Number of Observations
<i>Idaho</i>						
Craigmont, ID	46.24, - 116.47	8	2012	2019	46	190
Genesee (Kambitsch Farm), ID	46.55, - 116.93	2	2011	2012	30	42
Genesee, ID	46.55, - 116.93	15	2005	2022	91	315
Moscow (Parker Farm), ID	46.74, -117	3	2007	2010	20	45
Moscow, ID	46.74, -117	13	2007	2019	70	289
Nez Perce, ID	46.23, - 116.24	3	2007	2009	27	62
<i>Manitoba</i>						
Arborg, MB	50.91, -97.22	7	2011	2023	62	117
Boissevain, MB	49.23, - 100.06	7	2010	2019	54	131
Carberry, MB	49.87, -99.36	5	2017	2023	45	95
Hamiota, MB	50.17, - 100.59	12	2010	2023	68	234
Melita, MB	49.27, -101	12	2010	2023	68	241
Morden, MB	49.19, -98.1	8	2010	2023	63	172
Portage, MB	49.97, -98.29	5	2017	2022	46	114
Roblin, MB	51.23, - 101.36	4	2017	2023	42	101

Appendix Table B.1 Continued. In-sample field pea trial location characteristics.

Location	Coordinates	Number of Years	Min Year	Max Year	Number of Cultivars	Number of Observations
Souris, MB	49.62, - 100.26	3	2021	2023	30	61
Swan River, MB	52.11, - 101.27	6	2018	2023	44	170
Thornhill, MB	49.2, -98.23	5	2011	2015	33	81
<i>Montana</i>						
Bozeman, MT	45.68, - 111.05	13	2008	2020	53	199
Broadview, MT	46.1, -108.88	9	2011	2020	58	164
Conrad, MT	48.17, - 111.95	14	2001	2023	121	368
Creston, MT	48.2, -114.32	9	2008	2018	48	156
Havre, MT	48.55, - 109.68	17	2007	2023	152	601
Huntley, MT	45.9, -108.3	13	2001	2023	76	231
Joplin, MT	48.56, - 110.77	3	2010	2012	22	43
Moccasin, MT	47.05, - 109.91	21	2001	2021	128	518
Richland, MT	48.82, - 106.05	15	2009	2023	158	651
Sidney, MT	47.71, - 104.16	10	2001	2018	68	190
<i>North Dakota</i>						
Arnegard, ND	47.81, - 103.44	3	2006	2010	16	26
Carrington, ND	47.45, -99.12	22	2001	2023	237	909
Crosby, ND	48.92, -103.3	8	2007	2016	27	80

Appendix Table B.1 Continued. In-sample field pea trial location characteristics.

Location	Coordinates	Number of Years	Min Year	Max Year	Number of Cultivars	Number of Observations
Dazey, ND	47.19, -98.2	7	2006	2012	33	90
Dickinson, ND	46.88, - 102.79	15	2001	2023	80	213
Golden Valley, ND	46.94, - 103.84	4	2013	2016	13	31
Hettinger, ND	46.01, - 102.66	13	2001	2023	103	323
Langdon, ND	48.75, -98.39	21	2001	2023	142	447
Mckenzie, ND	47.87, - 103.04	4	2012	2016	15	33
Minot, ND	48.23, -101.3	14	2001	2023	136	414
New Town, ND	47.98, - 102.49	4	2006	2010	18	37
Powers Lake, ND	48.56, - 102.65	3	2006	2008	14	28
Ray, ND	48.34, - 103.16	4	2006	2010	20	40
Sheridan County, ND	47.58, - 100.34	2	2010	2013	6	12
Stanley, ND	48.32, - 102.39	3	2008	2012	15	27
Williston, ND	48.18, - 103.63	12	2001	2016	116	397
Wishek, ND	46.26, -99.56	9	2004	2012	34	103
<i>Saskatchewan</i>						
Avonlea, SK	50.01, - 105.06	3	2021	2023	21	54
Codette, SK	53.16, - 104.01	3	2021	2023	21	54
Glaslyn, SK	53.36, - 108.37	9	2011	2022	42	192

Appendix Table B.1 Continued. In-sample field pea trial location characteristics.

Location	Coordinates	Number of Years	Min Year	Max Year	Number of Cultivars	Number of Observations
Hodgeville, SK	50.11, - 106.96	5	2011	2019	38	114
Indian Head, SK	50.32, -103.4	8	2011	2019	38	181
Kamsack, SK	51.56, - 101.89	5	2015	2019	33	124
Limerick, SK	49.65, - 106.27	3	2015	2019	32	75
Lucky Lake, SK	51, -107.15	8	2015	2023	38	178
Meath Park, SK	53.43, - 105.37	8	2011	2019	38	178
Melfort, SK	52.86, - 104.61	9	2011	2019	38	201
Milden, SK	51.29, - 107.31	3	2011	2014	26	55
Moose Jaw, SK	50.39, - 105.55	4	2020	2023	31	80
Redvers, SK	49.57, -101.7	3	2021	2023	21	54
Rosthern, SK	52.66, - 106.34	12	2011	2023	43	260
Saskatoon (Skarsgard), SK	52.14, - 106.69	2	2017	2019	30	52
Saskatoon (Sutherland), SK	52.14, -106.6	12	2011	2023	43	232
Saskatoon, SK	52.14, - 106.69	4	2018	2022	32	82
Scott, SK	52.29, - 108.95	10	2011	2023	43	212
St. Brieux, SK	52.63, - 104.89	4	2020	2023	31	80
Swift Current, SK	50.29, - 107.79	12	2011	2022	43	265
Yorkton, SK	51.21, - 102.46	3	2011	2014	26	59

Appendix Table B.1 Continued. In-sample field pea trial location characteristics.

Location	Coordinates	Number of Years	Min Year	Max Year	Number of Cultivars	Number of Observations
<i>Washington</i>						
Dusty, WA	46.81, - 117.65	3	2011	2013	36	72
Farmington, WA	47.09, - 117.05	5	2011	2023	57	122
Palouse, WA	46.91, - 117.08	5	2011	2015	39	115
Walla Walla, WA	46.08, - 118.31	7	2011	2021	84	181
<i>Total</i>	NA	23	2001	2023	376	12063

Notes: Variety trial data was obtained from annual field trial reports published by university extension services (U.S.) and producer associations (Canada). Min year is the first year a location appears in the data and max year is the last. Number of observations is the number of unique yield observations at a location.

Appendix Table B.2. In-sample lentil trial location characteristics.

Location	Coordinates	Number of Years	Min Year	Max Year	Number of Cultivars	Number of Observations
<i>Idaho</i>						
Craigmont, ID	46.24, -116.47	8	2010	2019	43	149
Genesee (Kambitsch Farm), ID	46.55, -116.93	4	2011	2014	30	71
Genesee (Zenner Farm), ID	46.55, -116.93	2	2012	2013	24	35
Genesee, ID	46.55, -116.93	13	2005	2022	41	179
Moscow (Parker Farm), ID	46.74, -117	2	2007	2008	6	12
Moscow, ID	46.74, -117	11	2007	2019	51	186
Nez Perce, ID	46.23, -116.24	3	2007	2009	18	40
<i>Manitoba</i>						
Hamiota, MB	50.17, -100.59	4	2015	2019	23	61
Melita, MB	49.27, -101	4	2015	2019	23	61
<i>Montana</i>						
Bozeman, MT	45.68, -111.05	12	2001	2020	39	122
Broadview, MT	46.1, -108.88	2	2011	2013	20	25
Conrad, MT	48.17, -111.95	14	2001	2021	40	146
Creston, MT	48.2, -114.32	11	2008	2018	31	118
Havre, MT	48.55, -109.68	15	2008	2022	61	223
Huntley, MT	45.9, -108.3	11	2001	2019	36	123
Joplin, MT	48.56, -110.77	3	2010	2012	21	45
Kalispell, MT	48.23, -114.34	3	2005	2007	21	46
Moccasin, MT	47.05, -109.91	19	2001	2020	68	312
Richland, MT	48.82, -106.05	16	2008	2023	62	289
Sidney, MT	47.71, -104.16	8	2001	2017	32	98

Appendix Table B.2 Continued. In-sample lentil trial location characteristics.

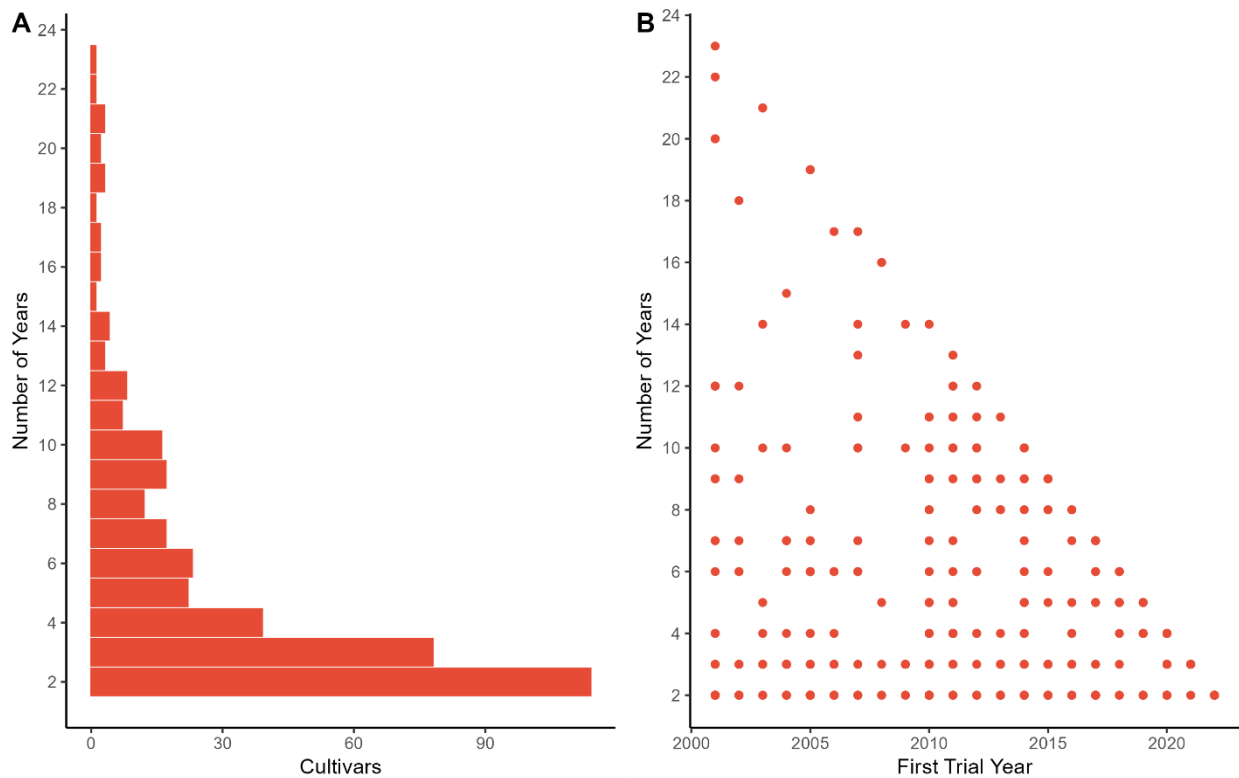
Location	Coordinates	Number of Years	Min Year	Max Year	Number of Cultivars	Number of Observations
<i>North Dakota</i>						
Arnegard, ND	47.81, -103.44	4	2006	2010	18	29
Carrington, ND	47.45, -99.12	19	2002	2022	44	256
Crosby, ND	48.92, -103.3	7	2006	2013	25	78
Dickinson, ND	46.88, -102.79	10	2011	2022	22	111
Golden Valley, ND	46.94, -103.84	3	2013	2015	21	40
Hettinger, ND	46.01, -102.66	12	2010	2022	33	174
Mckenzie, ND	47.87, -103.04	3	2010	2014	17	26
Minot, ND	48.23, -101.3	12	2005	2023	43	138
New Town, ND	47.98, -102.49	5	2006	2010	22	49
Powers Lake, ND	48.56, -102.65	2	2007	2008	11	17
Ray, ND	48.34, -103.16	4	2007	2010	22	44
Sheridan County, ND	47.58, -100.34	2	2010	2012	12	22
Stanley, ND	48.32, -102.39	6	2008	2013	22	57
Williston, ND	48.18, -103.63	10	2005	2015	45	273
<i>Saskatchewan</i>						
Avonlea, SK	50.01, -105.06	2	2021	2023	17	30
Elrose, SK	51.2, -108.03	9	2011	2023	50	220
Hodgeville, SK	50.11, -106.96	6	2010	2019	49	162
Limerick, SK	49.65, -106.27	6	2012	2019	49	165
Lucky Lake, SK	51, -107.15	5	2015	2019	32	138
Melfort, SK	52.86, -104.61	6	2011	2019	49	169
Milden, SK	51.29, -107.31	4	2011	2014	41	112
Moose Jaw, SK	50.39, -105.55	4	2012	2022	47	87
Rosthern, SK	52.66, -106.34	12	2010	2023	50	284
Saskatoon (Floral), SK	52.14, -106.69	4	2012	2021	43	89

Appendix Table B.2 Continued. In-sample lentil trial location characteristics.

Location	Coordinates	Number of Years	Min Year	Max Year	Number of Cultivars	Number of Observations
Saskatoon (Skarsgard), SK	52.14, -106.69	2	2017	2019	2	3
Saskatoon (Sutherland), SK	52.14, -106.6	11	2010	2020	50	311
Saskatoon, SK	52.14, -106.69	3	2015	2019	30	80
Scott, SK	52.29, -108.95	6	2013	2022	41	144
St. Brieux, SK	52.63, -104.89	3	2021	2023	17	44
Swift Current, SK	50.29, -107.79	12	2010	2022	50	305
<i>Washington</i>						
Dusty, WA	46.81, -117.65	3	2011	2013	28	57
Farmington, WA	47.09, -117.05	5	2011	2023	33	83
Palouse, WA	46.91, -117.08	5	2011	2015	33	89
Walla Walla, WA	46.08, -118.31	7	2011	2021	41	117
<i>Total</i>	NA	23	2001	2023	139	6344

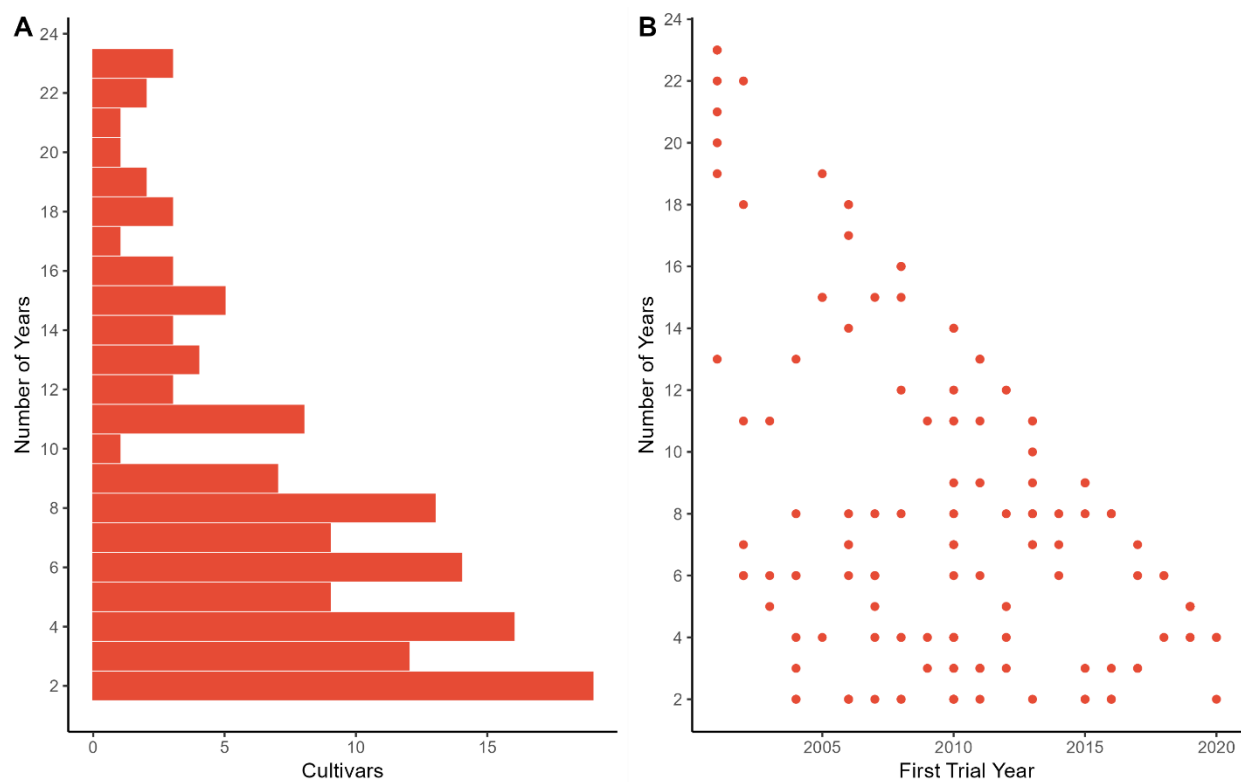
Notes: Variety trial data was obtained from annual field trial reports published by university extension services (U.S.) and producer associations (Canada). Min year is the first year a location appears in the data and max year is the last. Number of observations is the number of unique yield observations at a location.

Appendix Figure B.1. Number of trial-years for each field pea cultivar and its relation to cultivar release.



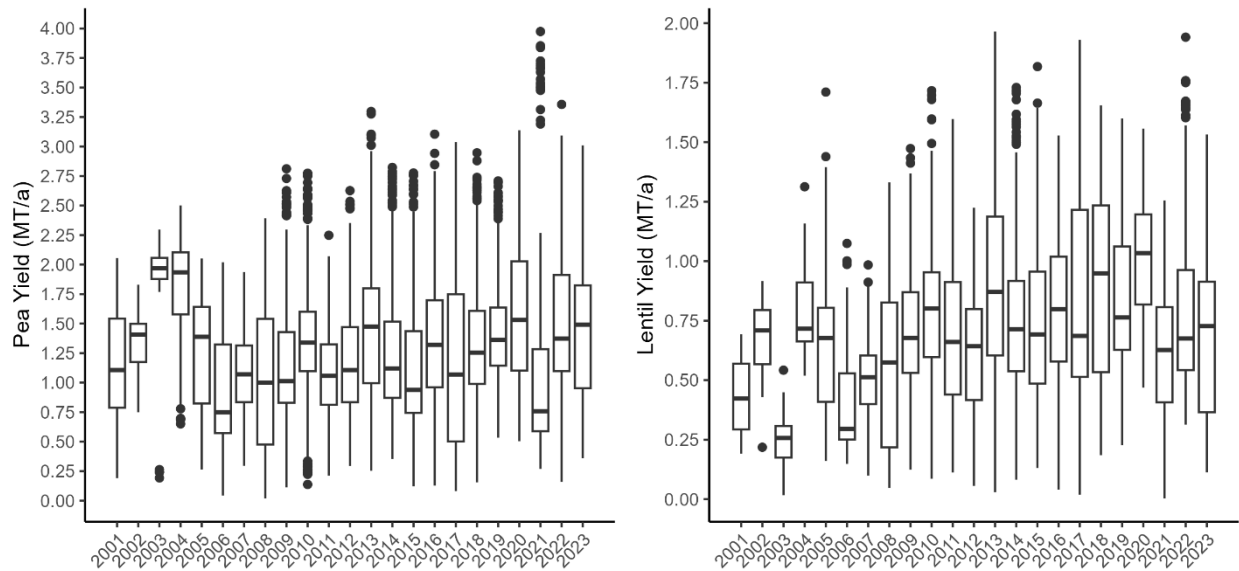
Notes: The number of years each field pea cultivar appeared in the trials were counted and plotted in panel (A). The number of years were plotted against the year in which the cultivar first appeared in a trial as shown in panel (B).

Appendix Figure B.2. Number of trial-years for each lentil cultivar and its relation to cultivar release.



Notes: The number of years each lentil cultivar appeared in the trials were counted and plotted in panel (A). The number of years were plotted against the year in which the cultivar first appeared in a trial as shown in panel (B).

Appendix Figure B.3. Spatial and temporal variation of field pea and lentil yield: 2001-2023.



Notes: Variety trial data was obtained from annual field trial reports published by university extension services (U.S.) and producer associations (Canada). The data varies at the variety-location-year level.

Appendix Table B.3. Mean (standard deviation) growing season dates, yield, daily temperatures, cumulative precipitation, and freeze exposure at field pea trial locations.

Location	Yield (MT)	Seeding Day	Harvest Day	Min Temp (°C)	Max Temp (°C)	Precipitation (cm)	Freeze
<i>Idaho</i>							
Craigmont, ID	0.78 (0.28)	120.13 (12.81)	236.05 (13.16)	9.08 (4.13)	23.06 (6.38)	18.07 (5.61)	0.33 (0.47)
Genesee, ID	1.07 (0.46)	116.41 (12.15)	228.38 (14.69)	9.43 (4.07)	24.28 (6.65)	13.65 (4.25)	0.24 (0.29)
Genesee (Kambitsch Farm), ID	1.55 (0.16)	126.44 (1.5)	231.59 (2.5)	8.79 (3.59)	23.54 (6.39)	13.74 (1.49)	0.09 (0.12)
Moscow, ID	0.9 (0.4)	121.34 (10.61)	240.04 (21.37)	8.85 (3.76)	24.77 (6.48)	11.44 (3.62)	0.23 (0.26)
Moscow (Parker Farm), ID	0.59 (0.37)	124.29 (6.27)	235.18 (4)	8.65 (3.63)	24.72 (6.6)	11.16 (3.07)	0.21 (0.15)
Nez Perce, ID	0.33 (0.2)	113.06 (5.47)	226.35 (1.27)	7.7 (4.58)	23.21 (7.16)	15.4 (4.6)	1.71 (1.89)
<i>Manitoba</i>							
Arborg, MB	1.85 (0.53)	135.11 (4.35)	238.89 (7.89)	11.81 (4.23)	23.47 (4.67)	23.74 (7.55)	0.27 (0.3)
Boissevain, MB	2.22 (0.44)	132.45 (5.46)	245.8 (10.44)	10.24 (4.03)	23.84 (4.79)	26.55 (7.75)	0.31 (0.36)
Carberry, MB	2.13 (0.64)	128.82 (2.69)	236.75 (5.06)	10.51 (4.63)	24.69 (5.17)	20.09 (5.12)	1.19 (1.23)
Hamiota, MB	1.84 (0.51)	131.59 (5.67)	244.98 (12.49)	9.75 (4.38)	23.3 (4.99)	28.16 (8.83)	0.96 (1.06)
Melita, MB	1.76 (0.43)	125.37 (6.62)	226.51 (10.24)	10.55 (4.71)	24.38 (5.27)	22.38 (7.74)	0.79 (0.97)
Morden, MB	1.8 (0.48)	133.57 (9.02)	243.76 (13.93)	11.79 (4.26)	25.03 (4.8)	25.75 (11.31)	0.59 (0.8)
Portage, MB	2.16 (0.43)	139.56 (9.46)	238.22 (6.94)	12.43 (3.97)	25.04 (4.62)	19.21 (5.91)	0.15 (0.21)

Appendix Table B.3 Continued. Mean (standard deviation) growing season dates, yield, daily temperatures, cumulative precipitation, and freeze exposure at field pea trial locations.

Location	Yield (MT)	Seeding Day	Harvest Day	Min Temp (°C)	Max Temp (°C)	Precipitation (cm)	Freeze
Roblin, MB	1.81 (0.38)	133.24 (8.64)	238.43 (6.37)	9.49 (4.53)	23.19 (5.21)	19.42 (5.87)	1.53 (1.77)
Souris, MB	2.91 (0.62)	136.54 (5.76)	244.62 (3.76)	11.54 (3.99)	25.43 (4.78)	25.3 (5.17)	0.29 (0.5)
Swan River, MB	2.03 (0.51)	134.74 (4.8)	239.5 (5.46)	10.37 (4.23)	23.97 (4.8)	20.86 (4.9)	0.44 (0.56)
Thornhill, MB	2 (0.42)	128.37 (5.29)	234.58 (4.65)	10.75 (4.44)	23.28 (5.09)	28.49 (5.58)	0.67 (0.69)
<i>Montana</i>							
Bozeman, MT	0.99 (0.29)	112.8 (7.79)	222.71 (11.13)	6.65 (4.34)	22.74 (7.01)	20.07 (4.61)	2.14 (1.92)
Broadview, MT	0.56 (0.24)	106.57 (8.34)	224.37 (8.27)	7.87 (5.04)	23.55 (7.52)	24.88 (7.78)	2.56 (2.07)
Conrad, MT	1.15 (0.43)	116.87 (11.05)	227.67 (13.1)	7.65 (4.45)	23.43 (6.61)	15.73 (4.01)	1.68 (1.9)
Creston, MT	1.84 (0.69)	114.8 (9.38)	229.24 (10.66)	6.77 (4.13)	23.63 (6.77)	15.3 (7.47)	1.75 (2.09)
Havre, MT	0.99 (0.31)	108.57 (5.74)	211.46 (13.86)	7.56 (5.16)	23.65 (7.04)	15.6 (6.68)	2.34 (1.94)
Huntley, MT	0.87 (0.39)	102.16 (15.73)	212.08 (9.62)	8.64 (5.63)	24.5 (7.76)	18.92 (6.76)	2.28 (3.33)
Joplin, MT	0.7 (0.29)	109.61 (10.41)	231.95 (6.91)	6.95 (4.87)	22.36 (7.27)	24.88 (3.66)	3.2 (3.13)
Moccasin, MT	0.82 (0.3)	108.09 (9.32)	217.31 (11.79)	6.36 (5.13)	21.98 (7.34)	20.98 (7.6)	3.79 (2.67)
Richland, MT	1.2 (0.6)	122.24 (10)	235.98 (19.37)	8.26 (4.7)	23.78 (6.08)	21.37 (9.36)	1.73 (1.57)
Sidney, MT	0.97 (0.55)	111.42 (6.3)	216.15 (10.04)	9.54 (5.58)	24.89 (6.66)	22.29 (8.63)	1.32 (1.27)

Appendix Table B.3 Continued. Mean (standard deviation) growing season dates, yield, daily temperatures, cumulative precipitation, and freeze exposure at field pea trial locations.

Location	Yield (MT)	Seeding Day	Harvest Day	Min Temp (°C)	Max Temp (°C)	Precipitation (cm)	Freeze
<i>North Dakota</i>							
Arnegard, ND	0.6 (0.31)	125.52 (4.77)	217.67 (3.12)	10.75 (4.91)	26.17 (6.98)	20.38 (8.96)	0.46 (0.63)
Carrington, ND	1.48 (0.42)	121.97 (8.1)	219.65 (8.71)	11 (5.23)	23.91 (5.87)	25.48 (8.44)	1.04 (1.45)
Crosby, ND	0.97 (0.39)	132.77 (8.51)	239.86 (12.4)	10.72 (4.24)	24.53 (5.3)	25.04 (3.62)	0.41 (0.5)
Dazey, ND	1.49 (0.38)	121.9 (11.04)	217.26 (11.04)	10.73 (5.18)	23.77 (5.75)	27.45 (12.43)	0.74 (1.6)
Dickinson, ND	0.87 (0.34)	117.44 (9.28)	214.2 (7.41)	9.26 (5.34)	24.23 (6.49)	23.4 (6.67)	1.36 (1.35)
Golden Valley, ND	1.05 (0.3)	132.94 (6.52)	242.13 (8.21)	11.03 (3.8)	25.72 (5.24)	25.27 (8.26)	0.32 (0.51)
Hettinger, ND	0.99 (0.47)	116.94 (8.67)	215.35 (8.89)	9.34 (5.35)	24.66 (6.66)	23.01 (8.66)	1.2 (0.89)
Langdon, ND	1.82 (0.41)	129.84 (8.98)	238.98 (11.06)	10.72 (4.47)	23.28 (5.26)	30.2 (7.97)	0.67 (0.9)
Mckenzie, ND	0.89 (0.25)	128.69 (5.33)	231.08 (7.42)	10.93 (4.47)	25.6 (5.51)	25.24 (0.64)	0.5 (0.35)
Minot, ND	1.2 (0.35)	127.96 (15.37)	233.08 (18.27)	11.47 (4.66)	25.01 (5.54)	22.67 (9.9)	0.58 (0.81)
New Town, ND	0.62 (0.35)	127.11 (4.28)	223.06 (3.14)	10.31 (4.53)	26 (6.27)	17.99 (6.11)	0.48 (0.49)
Powers Lake, ND	0.76 (0.27)	129.2 (2.02)	230.33 (4.84)	10.13 (4.34)	25.16 (6.05)	21.16 (6.54)	0.44 (0.49)
Ray, ND	0.66 (0.14)	127.73 (4.42)	222.65 (2.63)	10.43 (4.52)	25.57 (6.04)	19.83 (6.54)	0.43 (0.67)
Sheridan County, ND	1.39 (0.27)	123.96 (5.49)	224.95 (4.49)	11.46 (4.46)	23.66 (5.66)	31.2 (4.74)	0.43 (0.22)
Stanley, ND	0.97 (0.18)	128.11 (6.4)	232.64 (6.82)	10.02 (4.41)	24.43 (5.74)	30.23 (3.42)	0.66 (1.05)

Appendix Table B.3 Continued. Mean (standard deviation) growing season dates, yield, daily temperatures, cumulative precipitation, and freeze exposure at field pea trial locations.

Location	Yield (MT)	Seeding Day	Harvest Day	Min Temp (°C)	Max Temp (°C)	Precipitation (cm)	Freeze
Williston, ND	0.94 (0.36)	118.89 (6.11)	213.45 (6.69)	9.83 (5.34)	24.67 (6.34)	18.55 (7.34)	1.15 (1.39)
Wishek, ND	1.02 (0.36)	120.31 (11.39)	219.18 (11.23)	10.12 (5.62)	23.83 (6.2)	27.11 (7.63)	1.38 (1.92)
<i>Saskatchewan</i>							
Avonlea, SK	1.64 (0.21)	129.5 (6.15)	234.58 (3.3)	9.89 (4.61)	25.6 (5.55)	16.01 (5.43)	0.99 (1.39)
Codette, SK	1.56 (0.62)	135.84 (6.2)	245.92 (3.28)	10.59 (3.92)	23.92 (4.89)	15.3 (4.53)	0.54 (0.93)
Glaslyn, SK	1.43 (0.32)	130.58 (6)	247.34 (5.17)	8.29 (3.8)	21.18 (4.32)	31.2 (5.23)	0.88 (1.28)
Hodgeville, SK	1.07 (0.21)	122.37 (9.54)	234 (9.38)	8.76 (4.33)	23.9 (5.47)	20.98 (9.65)	1.62 (2.74)
Indian Head, SK	1.32 (0.35)	124.31 (7.84)	232.63 (7.44)	9.45 (4.55)	22.51 (5.24)	24.19 (5.6)	1.27 (2.29)
Kamsack, SK	1.42 (0.22)	123.53 (7.03)	233.79 (6.39)	9.03 (4.81)	22.67 (5.15)	21.46 (6.97)	2.01 (2.73)
Limerick, SK	0.79 (0.18)	114.49 (7.39)	223.61 (5.48)	7.44 (5.26)	23.3 (6.31)	17.55 (9.38)	3.28 (3.09)
Lucky Lake, SK	0.79 (0.21)	123.43 (8.37)	234.78 (6.17)	9.18 (4.6)	24.46 (5.66)	16.8 (7.32)	1.54 (2.16)
Meath Park, SK	1.33 (0.43)	129.97 (7.92)	245.03 (7.91)	9.19 (4.08)	21.8 (4.57)	27.43 (5.7)	1.02 (2.35)
Melfort, SK	1.73 (0.26)	128.94 (7.9)	242.68 (7.51)	9.26 (4.24)	22.19 (4.66)	25.25 (6.89)	1.16 (2.17)
Milden, SK	1.06 (0.16)	129.01 (3.56)	239.34 (3.77)	9.53 (4.04)	22.54 (4.92)	26.28 (5.63)	0.49 (0.54)
Moose Jaw, SK	1.18 (0.29)	128.86 (5.61)	235.43 (2.95)	9.67 (4.72)	25.44 (5.53)	13.48 (2.15)	1.21 (1.28)
Redvers, SK	0.83 (0.14)	130.85 (6.2)	232.25 (3.69)	10.62 (4.7)	24.65 (5.43)	24.24 (10.21)	0.94 (1.5)

Appendix Table B.3 Continued. Mean (standard deviation) growing season dates, yield, daily temperatures, cumulative precipitation, and freeze exposure at field pea trial locations.

Location	Yield (MT)	Seeding Day	Harvest Day	Min Temp (°C)	Max Temp (°C)	Precipitation (cm)	Freeze
Rosthern, SK	1.53 (0.39)	129.05 (7.86)	242.73 (6.76)	9.21 (4.14)	22.74 (4.66)	24.15 (6.26)	1.09 (1.9)
Saskatoon, SK	1.74 (0.36)	130.37 (5.11)	242.46 (2.68)	9.49 (4.32)	24.26 (5.54)	16.52 (4.58)	1.06 (1)
Saskatoon (Skarsgard), SK	1.3 (0.32)	117.72 (9.02)	230.33 (5.51)	7.57 (5.09)	22.25 (5.31)	18.13 (0.8)	3.25 (4.24)
Saskatoon (Sutherland), SK	1.5 (0.51)	127.3 (7.62)	240.15 (6.57)	9.29 (4.31)	23.47 (5.08)	20.2 (5.29)	1.14 (1.8)
Scott, SK	1.2 (0.35)	126.89 (7.98)	241.39 (7.13)	8.77 (4.05)	22.78 (5.03)	22.3 (6.62)	1.08 (2.02)
St. Brieux, SK	1.3 (0.46)	133.39 (5.17)	243.45 (2.87)	9.98 (4.13)	23.23 (5)	21.08 (4.09)	1.01 (1.1)
Swift Current, SK	1.45 (0.4)	123.4 (7.75)	234.23 (6.84)	8.94 (4.55)	24 (5.79)	18.35 (8.18)	1.42 (1.79)
Yorkton, SK	1.61 (0.32)	135.01 (0.82)	243.74 (3.12)	10.59 (3.8)	22.82 (4.43)	29.97 (10.37)	0.19 (0.33)
<i>Washington</i>							
Dusty, WA	1 (0.17)	112.74 (8.25)	224.14 (9.66)	8.33 (4.19)	24.99 (6.74)	12.42 (5.91)	0.64 (0.16)
Farmington, WA	1.04 (0.25)	122.54 (7.68)	232.81 (7.27)	8.58 (3.79)	24.89 (6.37)	11.55 (3.23)	0.36 (0.41)
Palouse, WA	1.15 (0.21)	119.21 (9.84)	230.69 (7.95)	8.42 (4.09)	25.2 (6.6)	10.51 (1.93)	0.53 (0.46)
Walla Walla, WA	1.13 (0.63)	107.87 (8.36)	218.77 (6.74)	11.43 (4.68)	26.81 (6.65)	11.08 (5.72)	0.05 (0.11)

Notes: Yield, seeding day, and harvest day were obtained from variety trial data collected from annual field trial reports published by university extension services (U.S.) and producer associations (Canada). Seeding and harvest day is denoted by the day of the year (e.g., 138 is equivalent to May 19). Weather data was obtained from Daymet. Data varies at the variety-location-year level.

Appendix Table B.4. Mean (standard deviation) growing season dates, yield, daily temperatures, cumulative precipitation, and freeze exposure at lentil trial locations.

Location	Yield (MT)	Seeding Day	Harvest Day	Min Temp (°C)	Max Temp (°C)	Precipitati on (cm)	Freeze
<i>Idaho</i>							
Craigmont, ID	0.53 (0.28)	123.65 (9.2)	244.58 (11.69)	8.89 (3.9)	22.98 (6.13)	18.26 (5.58)	0.32 (0.38)
Genesee, ID	0.58 (0.19)	117.27 (9.21)	235.01 (16.82)	9.54 (4.04)	24.36 (6.53)	13.34 (4.21)	0.32 (0.63)
Genesee (Kambitsch Farm), ID	0.82 (0.3)	123.15 (5.77)	231.45 (6.21)	9.25 (3.9)	24.52 (6.56)	11.83 (3.35)	0.23 (0.35)
Genesee (Zenner Farm), ID	0.61 (0.25)	101.94 (9.96)	229.87 (3.49)	8.35 (4.76)	23.12 (7.56)	18.94 (0.81)	1.76 (2.14)
Moscow, ID	0.54 (0.33)	124.27 (8.28)	252.01 (14.34)	9.05 (3.56)	25.31 (6.14)	10.21 (2.14)	0.21 (0.3)
Moscow (Parker Farm), ID	0.47 (0.17)	121.82 (6.01)	237.42 (2.5)	8.63 (3.67)	25.13 (6.62)	10.12 (3.51)	0.23 (0.21)
Nez Perce, ID	0.22 (0.13)	115.45 (4.47)	229.8 (3.28)	7.97 (4.45)	23.6 (7.1)	15.4 (4.6)	1.32 (1.78)
<i>Manitoba</i>							
Hamiota, MB	1.17 (0.33)	127.42 (1.9)	250.32 (14.44)	9.18 (4.6)	23.03 (5)	29.46 (9.71)	1.42 (1.06)
Melita, MB	1.33 (0.17)	124.82 (3.72)	229.26 (4.58)	10.06 (4.48)	24.61 (5.05)	22.08 (7.43)	0.74 (0.45)
<i>Montana</i>							
Bozeman, MT	0.73 (0.29)	114.07 (8.22)	227.16 (11.12)	6.91 (4.23)	23.36 (6.83)	19.67 (4.23)	1.76 (1.7)
Broadview, MT	0.41 (0.1)	111.78 (3)	226.9 (5.5)	8.28 (5.11)	23.73 (7.43)	32.3 (6.77)	2.45 (1.65)

Appendix Table B.4 Continued. Mean (standard deviation) growing season dates, yield, daily temperatures, cumulative precipitation, and freeze exposure at lentil trial locations.

Location	Yield (MT)	Seeding Day	Harvest Day	Min Temp (°C)	Max Temp (°C)	Precipitation (cm)	Freeze
Conrad, MT	0.7 (0.33)	117.19 (13.54)	235.37 (15.67)	7.67 (4.49)	23.58 (6.67)	16.71 (4.36)	1.84 (1.95)
Creston, MT	0.93 (0.35)	114.98 (8.64)	240.25 (10.19)	6.75 (3.99)	23.58 (6.8)	17.03 (7.28)	1.78 (1.88)
Havre, MT	0.67 (0.29)	108.54 (6.32)	217.85 (13.9)	7.66 (5.27)	23.93 (7.23)	15.88 (6.83)	2.62 (1.93)
Huntley, MT	0.38 (0.18)	104.82 (13.44)	219.99 (10.97)	9 (5.41)	25.13 (7.82)	18.25 (6.95)	1.7 (2.15)
Joplin, MT	0.54 (0.29)	109.44 (10.15)	233.65 (5.19)	6.97 (4.86)	22.44 (7.24)	25.11 (3.44)	3.2 (3.13)
Kalispell, MT	0.57 (0.23)	111.26 (6.07)	218.4 (6.09)	6.01 (4.31)	23.53 (7.08)	19 (6.24)	2.21 (1.8)
Moccasin, MT	0.54 (0.22)	109.21 (9.76)	222.72 (13.04)	6.59 (5.04)	22.25 (7.25)	22.12 (7.62)	3.46 (2.49)
Richland, MT	0.59 (0.29)	121.46 (10.89)	242.87 (22.32)	8.06 (4.85)	23.59 (6.34)	22.14 (10.12)	2.37 (2.3)
Sidney, MT	0.54 (0.28)	111.57 (6.34)	217.96 (11.52)	9.43 (5.5)	24.7 (6.69)	23.32 (8.88)	1.18 (1.16)
<i>North Dakota</i>							
Arnegard, ND	0.72 (0.41)	125.09 (4.09)	222.32 (7.83)	10.14 (4.96)	25.57 (6.6)	22 (8.01)	0.57 (0.56)
Carrington, ND	0.82 (0.31)	125.59 (8.7)	235.01 (18.65)	11.4 (4.87)	24.36 (5.52)	25.78 (11.51)	0.67 (0.77)
Crosby, ND	0.67 (0.31)	135.49 (5.5)	239.38 (16.76)	11.22 (3.98)	24.96 (5.47)	24.15 (8.14)	0.17 (0.33)
Dickinson, ND	0.78 (0.26)	122.32 (11.84)	223.66 (9.7)	9.9 (5.14)	24.9 (6.23)	24.63 (9.02)	1.13 (1.03)
Golden Valley, ND	1 (0.29)	132.85 (7.29)	259.91 (16.99)	10.32 (4.33)	24.6 (5.95)	33.15 (8.01)	0.81 (0.51)

Appendix Table B.4 Continued. Mean (standard deviation) growing season dates, yield, daily temperatures, cumulative precipitation, and freeze exposure at lentil trial locations.

Location	Yield (MT)	Seeding Day	Harvest Day	Min Temp (°C)	Max Temp (°C)	Precipitation (cm)	Freeze
Hettinger, ND	0.9 (0.29)	113.55 (11.27)	224.44 (7.48)	9.24 (5.65)	24.46 (6.99)	25.99 (8.1)	2.25 (2.75)
Mckenzie, ND	0.76 (0.17)	128.95 (6.38)	249.2 (34.27)	9.82 (4.99)	23.86 (6.39)	30.01 (4.87)	1.26 (1)
Minot, ND	0.72 (0.26)	128.26 (8.66)	237.94 (17.21)	11.33 (4.44)	25.07 (5.45)	24.03 (10.32)	0.51 (0.84)
New Town, ND	0.67 (0.28)	127.96 (4.11)	226.32 (6.77)	10.03 (4.5)	25.55 (6.1)	19.05 (5.8)	0.53 (0.44)
Powers Lake, ND	0.64 (0.08)	128 (1)	233.5 (0.5)	9.84 (4.55)	24.51 (6.15)	24.75 (2.92)	0.57 (0.62)
Ray, ND	0.71 (0.2)	127.97 (4.4)	228.86 (9.01)	9.89 (4.66)	24.65 (5.82)	23.15 (3.88)	0.63 (0.68)
Sheridan County, ND	1.01 (0.11)	120.64 (1.5)	242.63 (12.47)	11.18 (4.52)	24.59 (5.97)	26.45 (1.98)	0.29 (0.42)
Stanley, ND	0.62 (0.18)	131.56 (5.99)	240.93 (8.68)	10.31 (4.19)	24.07 (5.35)	32.08 (7.64)	0.54 (0.82)
Williston, ND	0.49 (0.24)	124.66 (7.27)	222.48 (11.04)	10.58 (5.02)	25.49 (6.16)	17.93 (7.76)	0.81 (1.29)
<i>Saskatchewan</i>							
Avonlea, SK	0.96 (0.1)	127.5 (5.51)	232.5 (5.51)	9.74 (4.85)	25.82 (5.74)	11.8 (0.24)	1.35 (1.75)
Elrose, SK	0.68 (0.2)	127.57 (4.03)	243.47 (5.82)	9.4 (3.91)	24.28 (5.19)	19.23 (7.18)	0.6 (0.85)
Hodgeville, SK	0.91 (0.23)	125.02 (4.22)	244.37 (2.25)	8.96 (4.12)	23.27 (5.32)	27.08 (6.43)	1.23 (0.89)
Limerick, SK	0.6 (0.16)	123.57 (3.79)	236.52 (6.62)	8.7 (4.45)	23.93 (5.67)	21.26 (10.06)	1.19 (1.14)
Lucky Lake, SK	0.56 (0.15)	124.2 (2.64)	242.06 (6.03)	8.95 (4.16)	24 (5.08)	19.46 (9.49)	1.07 (1.15)

Appendix Table B.4 Continued. Mean (standard deviation) growing season dates, yield, daily temperatures, cumulative precipitation, and freeze exposure at lentil trial locations.

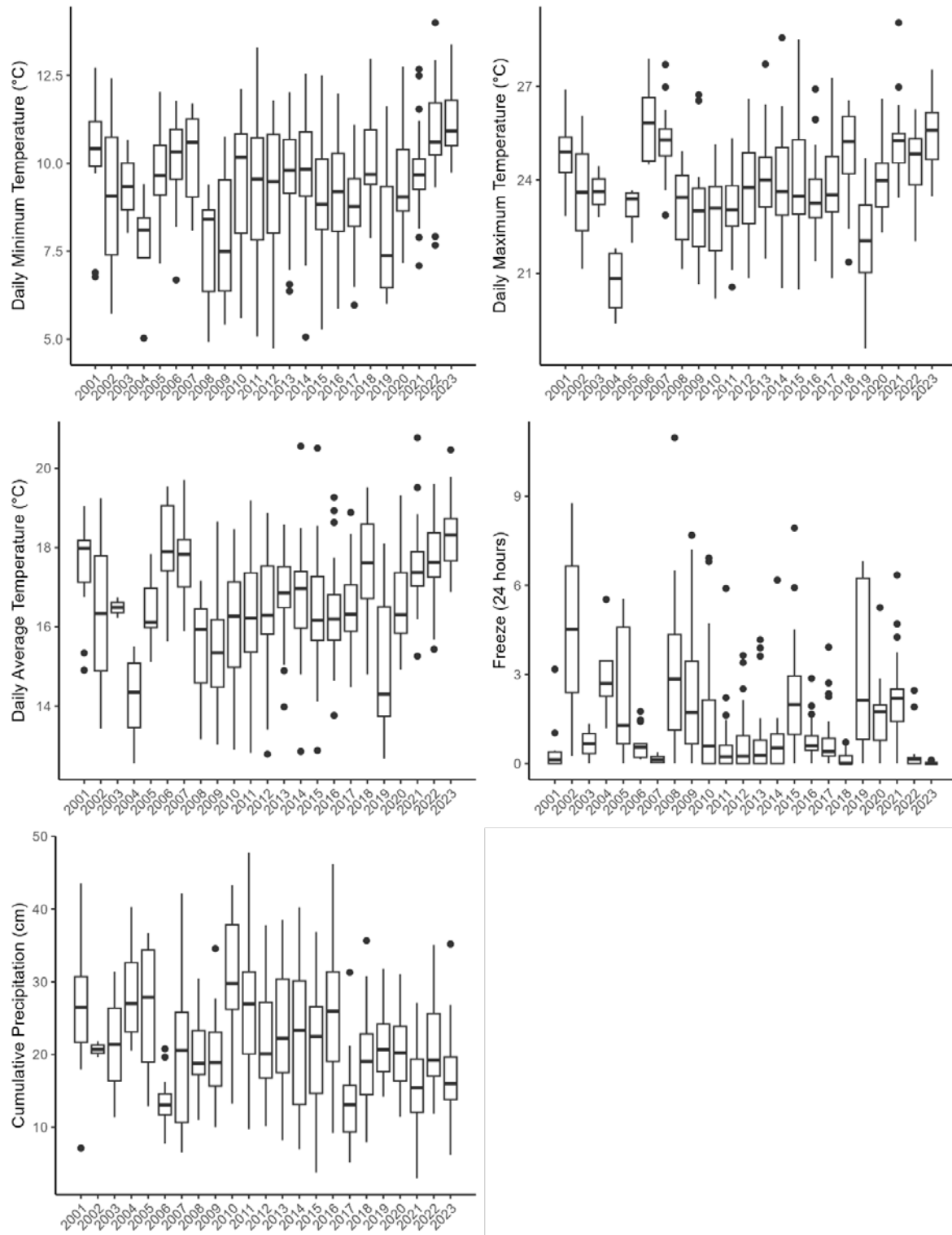
Location	Yield (MT)	Seeding Day	Harvest Day	Min Temp (°C)	Max Temp (°C)	Precipitati on (cm)	Freeze
Melfort, SK	1.16 (0.34)	130.6 (3.62)	248.52 (5.14)	9.35 (3.72)	22.33 (4.26)	23.29 (5.67)	0.37 (0.36)
Milden, SK	0.78 (0.34)	129.02 (3.92)	245.87 (5.62)	9.55 (3.82)	22.72 (4.87)	25.85 (6.4)	0.33 (0.18)
Moose Jaw, SK	0.63 (0.18)	125.08 (3.1)	236.45 (6.38)	9.37 (4.98)	24.75 (5.92)	17.43 (6.62)	1.23 (1.2)
Rosthern, SK	1 (0.3)	129.86 (3.92)	247.66 (6.09)	9.31 (3.98)	22.78 (4.88)	25.12 (8.87)	0.78 (0.85)
Saskatoon, SK	0.87 (0.28)	125.7 (0.96)	241.88 (5.48)	8.64 (4.29)	23.18 (4.72)	23.2 (6.4)	1.03 (0.77)
Saskatoon (Floral), SK	0.87 (0.33)	125.71 (1.93)	242.56 (6.05)	9.44 (4.42)	23.34 (5.43)	23.35 (8.31)	1.18 (0.87)
Saskatoon (Skarsgard), SK	1 (0.36)	126.05 (1)	242.8 (6.51)	8.37 (3.9)	23.02 (4.35)	19.72 (3.06)	0.64 (0.55)
Saskatoon (Sutherland), SK	1.01 (0.34)	127.89 (3.37)	246.55 (5.48)	9.2 (4.03)	22.84 (4.78)	24.76 (7.97)	0.7 (0.66)
Scott, SK	0.79 (0.21)	127.32 (3.21)	249.39 (5.8)	8.74 (3.94)	22.89 (4.99)	21.32 (5.66)	0.83 (0.88)
St. Brieux, SK	1.18 (0.37)	132.35 (4.06)	243.88 (6.63)	10.1 (4.1)	23.36 (5.16)	21.38 (8.57)	0.69 (1.09)
Swift Current, SK	1.03 (0.33)	124.16 (3.82)	241.07 (6.36)	9.05 (4.33)	23.82 (5.78)	21.34 (9.96)	1.1 (0.94)
<i>Washington</i>							
Dusty, WA	0.52 (0.23)	114.66 (3.65)	234.77 (5.01)	8.69 (4.08)	25.88 (6.69)	12 (4.98)	0.58 (0.21)

Appendix Table B.4 Continued. Mean (standard deviation) growing season dates, yield, daily temperatures, cumulative precipitation, and freeze exposure at lentil trial locations.

Location	Yield (MT)	Seeding Day	Harvest Day	Min Temp (°C)	Max Temp (°C)	Precipitation (cm)	Freeze
Farmington, WA	0.64 (0.24)	117.97 (4.03)	237.32 (5.18)	8.57 (3.88)	24.76 (6.5)	13.2 (4.94)	0.37 (0.38)
Palouse, WA	0.81 (0.23)	115.03 (4.04)	235.32 (5.93)	8.43 (4.1)	25.13 (6.68)	11.94 (3.17)	0.53 (0.28)
Walla Walla, WA	0.48 (0.26)	112.34 (3.85)	231.31 (6.44)	12.1 (4.56)	27.84 (6.49)	10.11 (5.67)	0.01 (0.02)

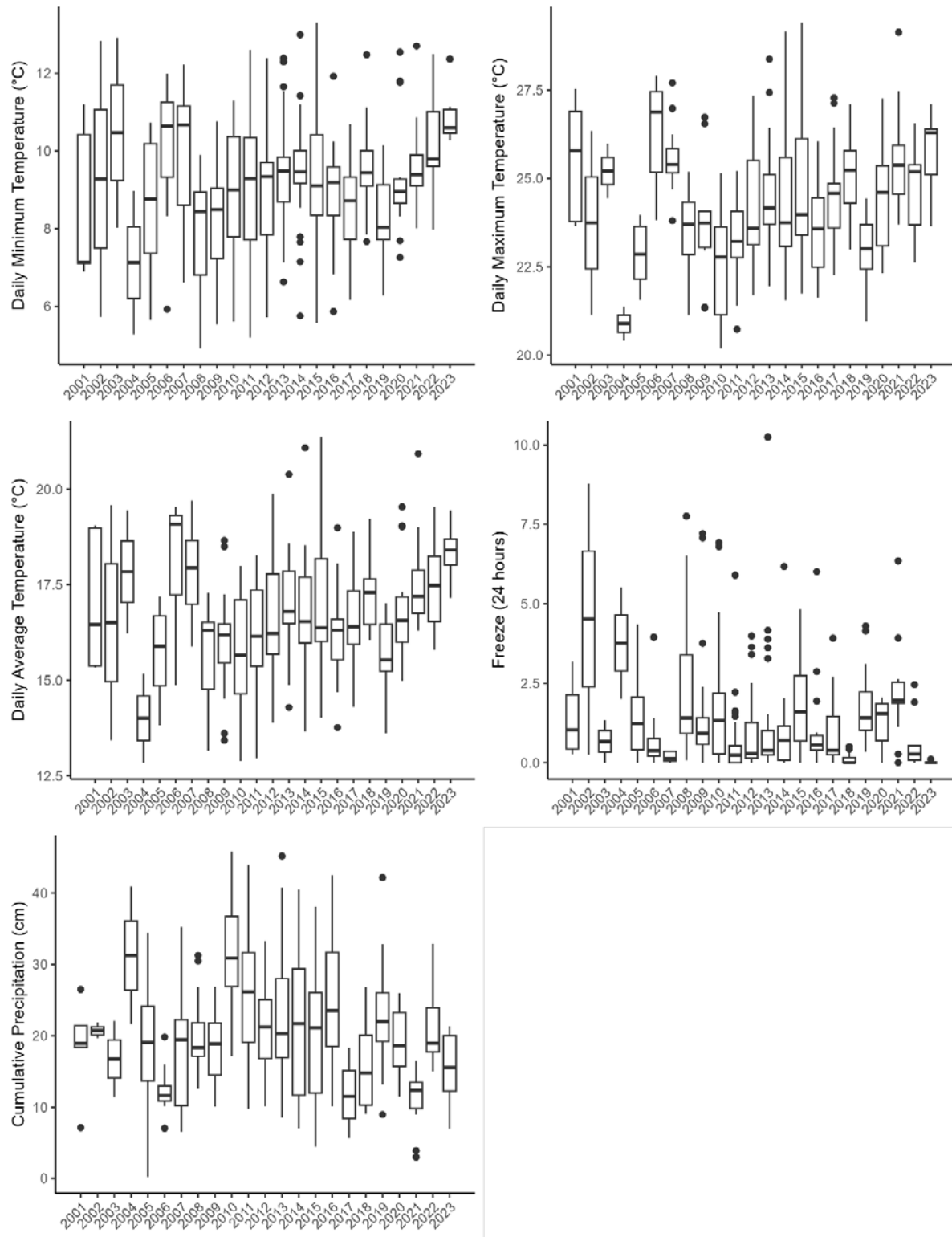
Notes: Yield, seeding day, and harvest day were obtained from variety trial data collected from annual field trial reports published by university extension services (U.S.) and producer associations (Canada). Seeding and harvest day is denoted by the day of the year (e.g., 138 is equivalent to May 19). Weather data was obtained from Daymet. Data varies at the variety-location-year level.

Appendix Figure B.4. Spatial and temporal variation of seasonal temperatures, freeze exposure, and precipitation by year in field pea trials: 2001-2023.



Notes: Weather data was obtained from Daymet. Weather variables were observed at the location-level and boxplots were constructed for each year.

Appendix Figure B.5. Spatial and temporal variation of seasonal temperatures, freeze exposure, and precipitation by year in lentil trials: 2001-2023.



Notes: Weather data was obtained from Daymet. Weather variables were observed at the location-level and boxplots were constructed for each year.

Appendix Table B.5. Optimal thresholds for field pea piecewise linear degree day model.

Variables	Thresholds	Mean (SD) DDs	Min DDs	Max DDs
DD Low	0-11°C	1093.30 (113.52)	802.33	1707.01
DD Medium	11-29°C	694.49 (102.56)	385.90	1076.79
DD High	>29°C	11.73 (11.62)	0	98.71

Notes: Thresholds were selected by looping over all combinations between 6-13°C for the first threshold and 27-36°C for the second threshold. The optimal thresholds were selected by identifying the combination that maximized the R-squared in the preferred model.

Appendix Table B.6. Optimal thresholds for lentil piecewise linear degree day model.

Variables	Thresholds	Mean (SD) DDs	Min DDs	Max DDs
DD Low	0-6°C	655.63 (81.77)	41.45	967.41
DD Medium	6-30°C	1208.88 (165.6)	78.87	1694.8
DD High	>30°C	9.12 (10.01)	0	63.7

Notes: Thresholds were selected by looping over all combinations between 6-13°C for the first threshold and 27-36°C for the second threshold. The optimal thresholds were selected by identifying the combination that maximized the R-squared in the preferred model.

Appendix Table B.7. Effects of abiotic stress on log field pea and lentil yield (MT/acre).

Variables	Pea Yield (MT/a)	Lentil Yield (MT/a)
DD Low	0.00142*** (0.00024)	-0.00053 (0.00075)
DD Medium	-0.00075** (0.00035)	0.00066 (0.00047)
DD High	-0.00993*** (0.00291)	-0.02586*** (0.00806)
Freeze	-0.03533** (0.01282)	0.01484 (0.01584)
Precipitation (cm)	0.04637*** (0.01144)	0.02425** (0.01127)
Precipitation Squared (cm)	-0.00090*** (0.00021)	-0.00058** (0.00021)
Trend	0.00278 (0.00481)	-0.00817 (0.00706)
Cultivar Fixed Effect	Yes	Yes
Location Fixed Effect	Yes	Yes
R-Squared	0.6	0.45
Observations	11,957	6,344

Notes: Standard errors are in parentheses and are clustered by year. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Appendix Table B.8. Out-of-sample comparison of alternative specifications.

Model	Out of sample RMSE (% reduction)	
	Field pea	Lentil
Average temperature	-0.01	0.57
Average min/max temperatures	0.70	1.28
Piecewise linear	4.95	3.14

Notes: Root mean squared errors (RMSE) are reported as a percentage reduction relative to a baseline model that does not include any weather variables. Each model was estimated using 80% of randomly selected data from 11,945 field pea observations and 6,343 lentil observations. Parameter estimates were then used to predict yields for the omitted 20% in each subsample.

Appendix Table B.9. Mean (standard deviation) field pea and lentil test weight by location.

Location	Field Pea Test Weight (lb/ac)	Lentil Test Weight (lb/ac)
<i>Idaho</i>		
Genesee, ID	64.7 (0.79)	61.35 (1.73)
<i>Manitoba</i>		
Roblin, MB	60.01 (0.03)	-
Swan River, MB	60.01 (0.03)	-
<i>Montana</i>		
Bozeman, MT	64.5 (1.02)	64.15 (1.58)
Broadview, MT	64.78 (1.06)	61.46 (1.9)
Conrad, MT	64.39 (1.72)	60.25 (3.72)
Creston, MT	63.89 (1.06)	61.43 (2.96)
Havre, MT	62.4 (1.91)	63.05 (1.86)
Huntley, MT	63.46 (2.3)	61.13 (2.61)
Joplin, MT	63.06 (1.99)	59.85 (2.38)
Moccasin, MT	64.17 (1.4)	62.66 (3.08)
Richland, MT	63.6 (1.64)	62.1 (2.85)
Sidney, MT	64.32 (0.91)	61.89 (2.04)
<i>North Dakota</i>		
Arnegard, ND	62.52 (6.57)	61.31 (2.42)
Carrington, ND	63.78 (1.25)	60.24 (2.86)
Crosby, ND	62.83 (2.16)	60.64 (2.41)
Dazey, ND	63.92 (1.03)	-
Dickinson, ND	64.42 (1.37)	60.76 (3.15)
Golden Valley, ND	61.03 (2.84)	58.11 (4.81)
Hettinger, ND	61.37 (2.52)	60.8 (3.32)

Appendix Table B.9 Continued. Mean (standard deviation) field pea and lentil test weight by location.

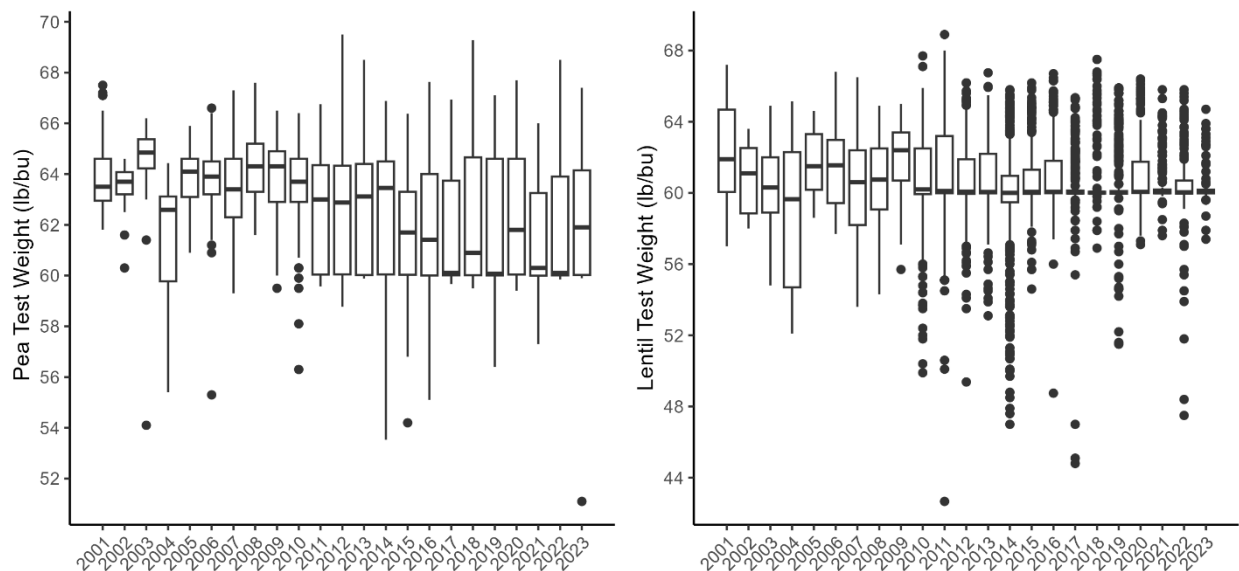
Location	Field Pea Test Weight (lb/ac)	Lentil Test Weight (lb/ac)
Langdon, ND	62.77 (1.56)	-
Mckenzie, ND	60.54 (2.52)	58.23 (5.39)
Minot, ND	64.26 (1.93)	59.78 (3.74)
New Town, ND	63.94 (1.37)	59.02 (7.98)
Powers Lake, ND	63.82 (2.18)	60.68 (2)
Ray, ND	63.66 (1.37)	61.51 (2.06)
Sheridan County, ND	63.56 (0.55)	59.37 (2.25)
Stanley, ND	64.68 (1.87)	60.86 (2.31)
Williston, ND	64.1 (1.45)	61.38 (2.08)
Wishek, ND	63.62 (1.07)	-
<i>Saskatchewan</i>		
Avonlea, SK	60 (0.03)	60 (0.05)
Codette, SK	59.99 (0.04)	-
Elrose, SK	-	60.02 (0.1)
Glaslyn, SK	60.01 (0.03)	-
Hodgeville, SK	60.01 (0.05)	60.02 (0.05)
Indian Head, SK	60.01 (0.04)	-
Kamsack, SK	60.01 (0.04)	-
Limerick, SK	60.02 (0.07)	60 (0.08)
Lucky Lake, SK	60 (0.07)	60.01 (0.1)
Meath Park, SK	60.02 (0.04)	-
Melfort, SK	60.01 (0.04)	60.01 (0.06)
Milden, SK	60.01 (0.05)	60.03 (0.11)
Moose Jaw, SK	60.01 (0.05)	60 (0.08)
Redvers, SK	60.01 (0.06)	-
Rosthern, SK	60.01 (0.04)	60.01 (0.06)
Saskatoon (Floral), SK	-	60 (0.06)

Appendix Table B.9 Continued. Mean (standard deviation) field pea and lentil test weight by location.

Location	Field Pea Test Weight (lb/ac)	Lentil Test Weight (lb/ac)
Saskatoon (Skarsgard), SK	60.01 (0.03)	60.07 (0.09)
Saskatoon (Sutherland), SK	60.01 (0.04)	60.01 (0.07)
Saskatoon, SK	60.01 (0.04)	60 (0.06)
Scott, SK	60.01 (0.05)	60.01 (0.08)
St. Brieux, SK	60 (0.04)	60 (0.07)
Swift Current, SK	60.01 (0.04)	60.01 (0.06)
Yorkton, SK	60.02 (0.03)	-
<i>Washington</i>		
Farmington, WA	63.69 (1.09)	61.05 (1.93)

Notes: Variety trial data was obtained from annual field trial reports published by university extension services (U.S.) and producer associations (Canada).

Appendix Figure B.6. Spatial and temporal variation of field pea and lentil test weight: 2001-2023.



Notes: Variety trial data was obtained from annual field trial reports published by university extension services (U.S.) and producer associations (Canada). Data varies at the variety-location-year level.

Appendix Table B.10. Mean (standard deviation) field pea protein content by location.

Location	Field Pea Protein Content (%)
<i>Manitoba</i>	
Arborg, MB	26.53 (2.25)
Boissevain, MB	23.95 (2.42)
Carberry, MB	25.35 (1.46)
Hamiota, MB	24.38 (2.36)
Melita, MB	24.1 (1.56)
Morden, MB	25.19 (2.04)
Portage, MB	24.85 (2.72)
Roblin, MB	24.31 (1.32)
Souris, MB	25.59 (1.6)
Swan River, MB	23.84 (2.38)
<i>Montana</i>	
Bozeman, MT	24.25 (2.68)
Broadview, MT	23.34 (1.45)
Conrad, MT	22.96 (3.09)
Havre, MT	24.78 (2.52)
Huntley, MT	20.55 (1.35)
Moccasin, MT	24.92 (1.31)
Richland, MT	24.8 (1.34)
<i>North Dakota</i>	
Arnegard, ND	22.67 (0.72)
Carrington, ND	24.46 (2.03)
Crosby, ND	23.31 (2.87)
Dazey, ND	24.17 (2.06)
Dickinson, ND	26.41 (2.16)

Appendix Table B.10 Continued. Mean (standard deviation) field pea protein content by location.

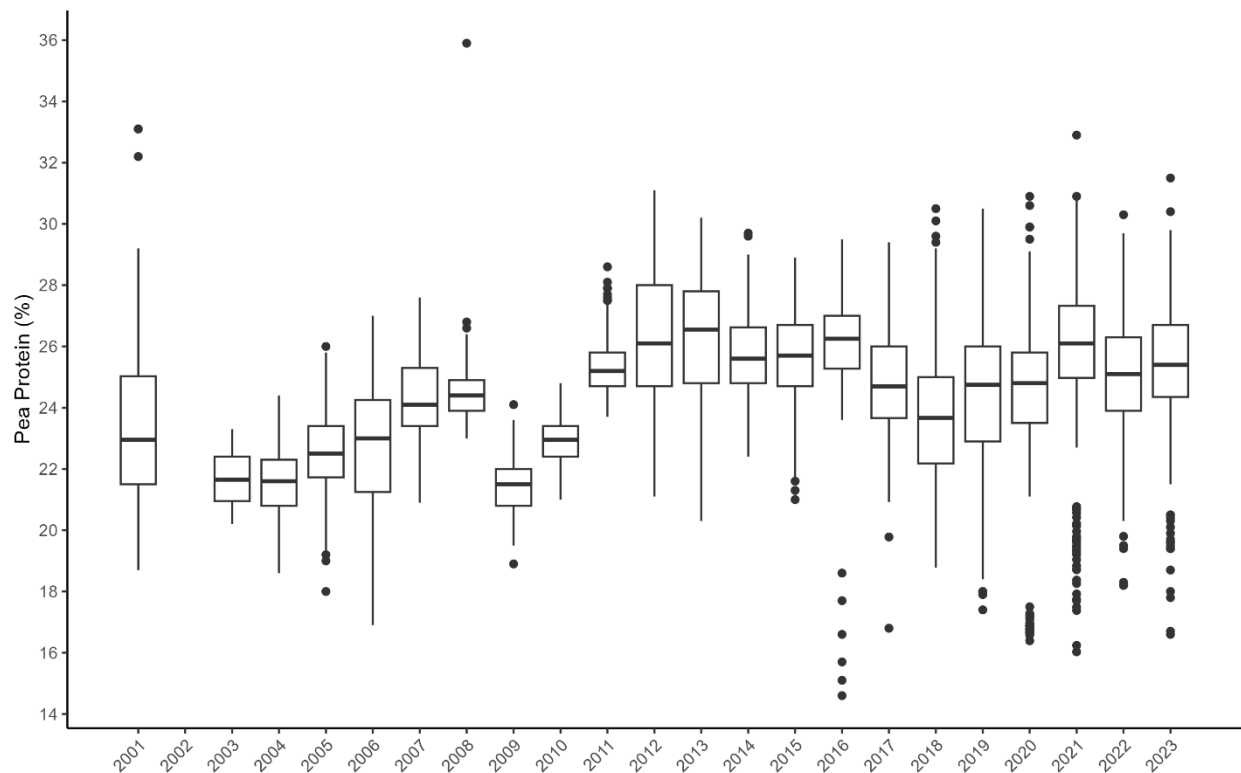
Location	Field Pea Protein Content (%)
Golden Valley, ND	23.93 (2.54)
Hettinger, ND	26.32 (1.62)
Langdon, ND	24.73 (1.9)
Mckenzie, ND	26.81 (1.35)
Minot, ND	25.17 (1.78)
New Town, ND	22.98 (2.52)
Powers Lake, ND	23.53 (1.56)
Ray, ND	23.48 (1.12)
Sheridan County, ND	22.68 (0.88)
Stanley, ND	24.22 (1.23)
Williston, ND	24.23 (2.99)
Wishek, ND	24.69 (2.47)
<i>Saskatchewan</i>	
Avonlea, SK	24.76 (1.01)
Codette, SK	22.63 (0.6)
Lucky Lake, SK	25.21 (0.59)
Moose Jaw, SK	24.66 (0.79)
Redvers, SK	19.73 (1.03)
Rosthern, SK	25.72 (0.56)
Saskatoon (Sutherland), SK	23.47 (1.56)
Saskatoon, SK	23.68 (0.78)
Scott, SK	23.85 (0.72)
St. Brieux, SK	22.81 (0.85)
Swift Current, SK	23.62 (0.72)

Appendix Table B.10 Continued. Mean (standard deviation) field pea protein content by location.

Location	Field Pea Protein Content (%)
<i>Washington</i>	
Farmington, WA	20.28 (1.83)
Walla Walla, WA	18.23 (1.5)

Notes: Variety trial data was obtained from annual field trial reports published by university extension services (U.S.) and producer associations (Canada).

Appendix Figure B.7. Spatial and temporal variation of field pea protein: 2001-2023.



Notes: Variety trial data was obtained from annual field trial reports published by university extension services (U.S.) and producer associations (Canada). Data varies at the variety-location-year level.

Appendix Table B.11. Effects of abiotic stress on field pea and lentil quality measures (log test weight (lb/bu) and log protein (%)).

Variables	Test Weight (lb/bu)		Protein (%)
	Field Pea	Lentil	Field Pea
DD Low	-0.00004 (0.00004)	-0.00004 (0.00008)	-0.00009 (0.00010)
DD Medium	0.00001 (0.00004)	-0.00003 (0.00004)	0.00018 (0.00016)
DD High	-0.00024 (0.00030)	-0.00004 (0.00055)	0.00204** (0.00094)
Freeze	-0.00090 (0.00061)	0.00109 (0.00128)	-0.00109 (0.00520)
Precipitation (cm)	0.00124* (0.00065)	0.00125 (0.00079)	0.00484 (0.00304)
Precipitation Squared (cm)	-0.00003** (0.00001)	-0.00003* (0.00002)	-0.00006 (0.00006)
Trend	-0.00024 (0.00024)	-0.00009 (0.00035)	0.00575*** (0.00172)
Cultivar Fixed Effect	Yes	Yes	Yes
Location Fixed Effect	Yes	Yes	Yes
R-Squared	0.7	0.51	0.6
Observations	8,803	4,977	4,427

Notes: Standard errors are in parentheses and are clustered by year. *, **, and *** denote statistically significance at the 10%, 5%, and 1% level, respectively.

Appendix C - Heterogeneous Effects of Yield and Quality for Herbicide Tolerant Lentil Varieties

Appendix Table C.1. Number of trials, observations, cultivars, and percentage of HT cultivars per year.

Year	Number of Trials	Number of Observations	Number of Cultivars	% HT Cultivars
2001	5	35	7	0
2002	2	19	13	0
2003	2	21	19	0
2004	2	23	20	0
2005	6	116	35	0
2006	8	130	37	0
2007	13	189	43	6.98
2008	18	197	36	16.67
2009	17	220	35	17.14
2010	26	435	52	23.08
2011	31	685	70	17.14
2012	34	672	65	18.46
2013	32	565	61	22.95
2014	28	523	58	25.86
2015	26	468	59	27.12
2016	23	443	69	26.09
2017	23	415	63	31.75
2018	21	356	53	37.74
2019	23	419	64	32.81
2020	15	228	47	40.43
2021	15	202	41	39.02
2022	14	154	39	35.9
2023	8	97	37	32.43

Notes: Variety trial data was obtained from annual field trial reports published by university extension services (U.S.) and producer associations (Canada).

Appendix Table C.2. Summary statistics for lentil yields.

Yield	Observations	Mean	Standard Deviation
Yield (All Trials)	6612	0.74	0.35
Yield (Conventional Cultivars)	4706	0.69	0.34
Yield (HT Cultivars)	1906	0.84	0.35

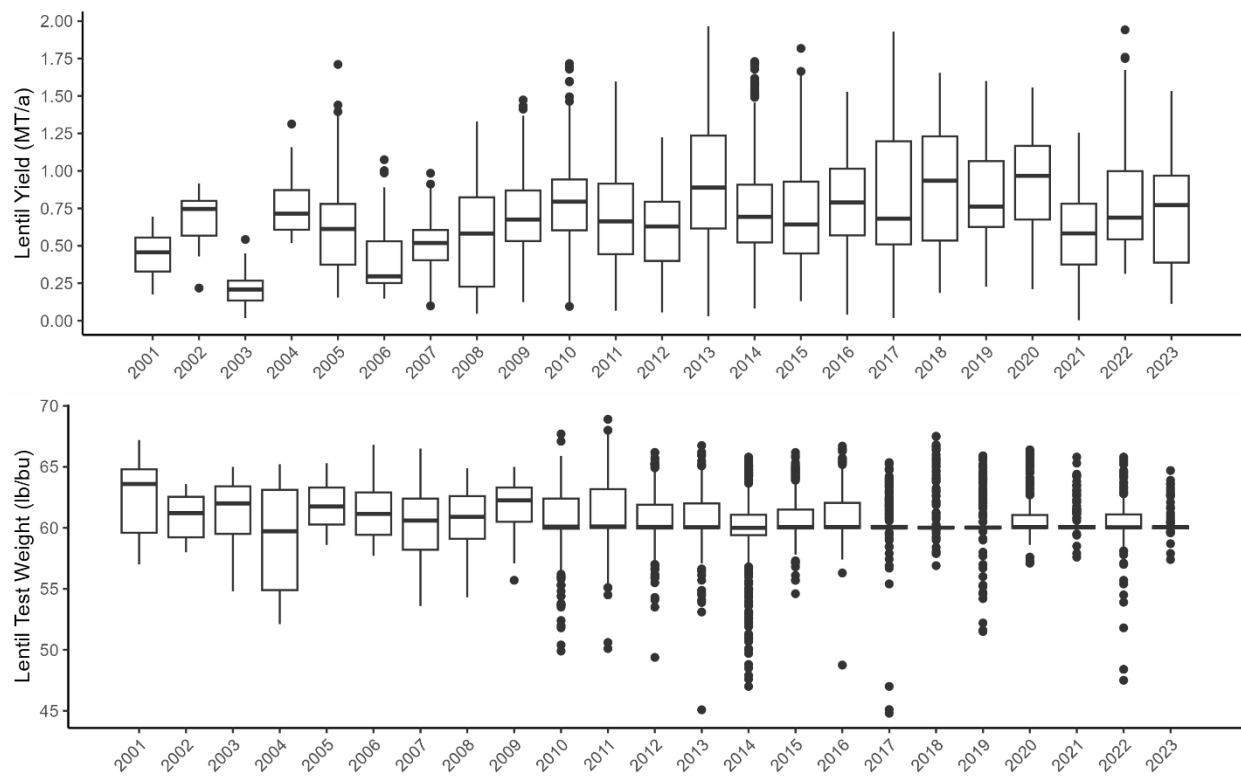
Notes: Yields are reported in metric tons per acre. Variety trial data was obtained from annual field trial reports published by university extension services (U.S.) and producer associations (Canada).

Appendix Table C.3. Summary statistics for lentil test weights.

Test Weight	Observations	Mean	Standard Deviation
Test Weight (All Trials)	6612	60.71	2.42
Test Weight (Conventional Cultivars)	4706	60.83	2.73
Test Weight (HT Cultivars)	1906	60.48	1.68

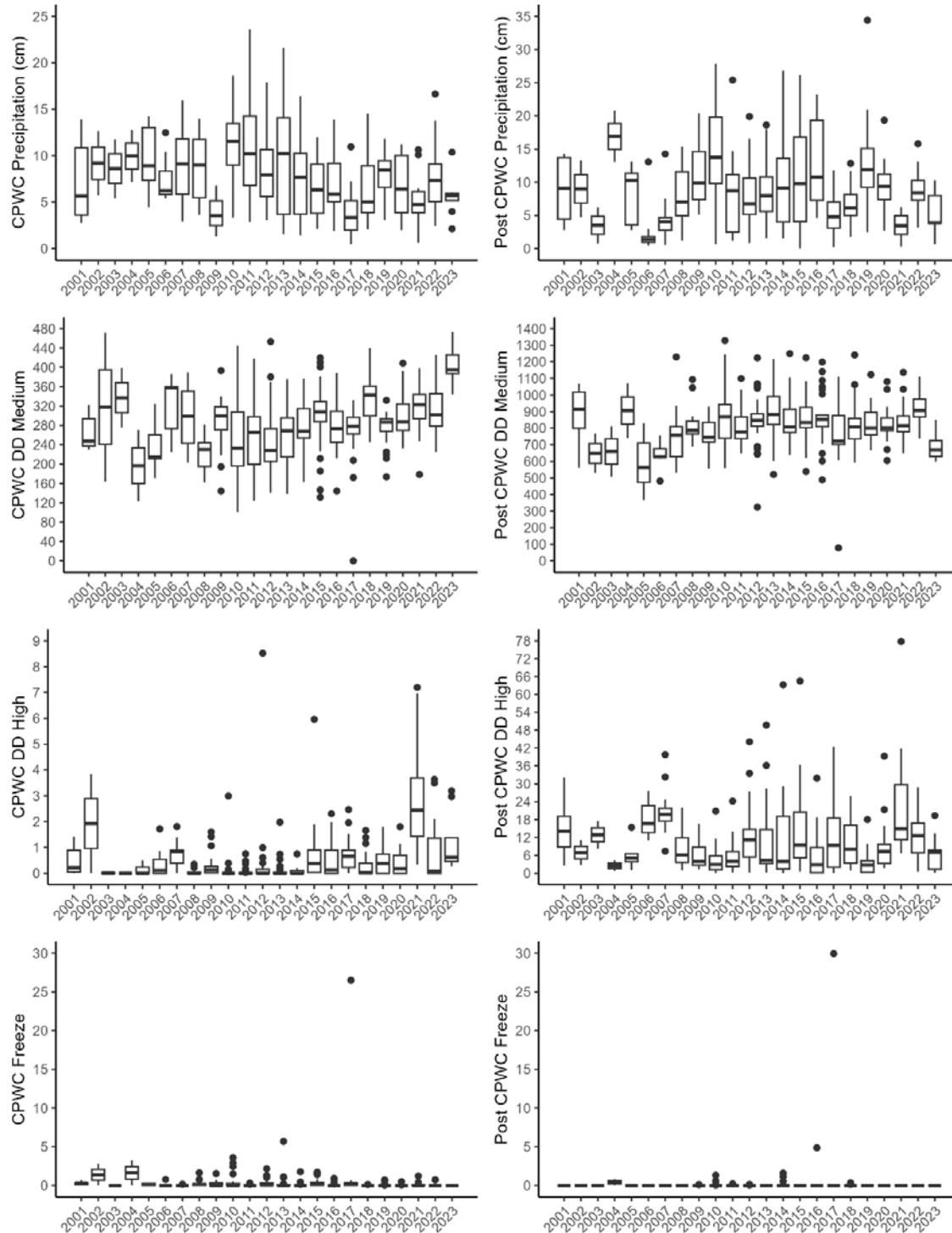
Notes: Test weights are reported in pounds per bushel. Variety trial data was obtained from annual field trial reports published by university extension services (U.S.) and producer associations (Canada).

Appendix Figure C.1. Spatial and temporal variation of lentil trial yield and test weight: 2001-2023.



Notes: Variety trial data was obtained from annual field trial reports published by university extension services (U.S.) and producer associations (Canada). Data varies at the variety-location-year level.

Appendix Figure C.2. Spatial and temporal variation of weather variables for CPWC and post CPWC: 2001-2023.



Notes: Weather data was obtained from Daymet. Degree day bins were calculated from interpolation between minimum and maximum temperatures. Weather variables were observed at the location-level and boxplots were constructed for each year. Weather variable construction is described in further detail in the text.