

Cover crop effects on maize productivity: Insights from statistical and process-based models

by

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The student author, whose presentation of the scholarship herein was approved by the program of study committee, is solely responsible for the content of this dissertation. The Graduate College will ensure this dissertation is globally accessible and will not permit alterations after a degree is conferred.

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DEDICATION

To the Marcillo-Peralta and Borja-Diaz families.

...For all who have left and all who will come.

TABLE OF CONTENTS

| | Page |
|---|------|
| ACKNOWLEDGEMENTS | v |
| ABSTRACT | vi |
| CHAPTER 1. GENERAL INTRODUCTION | 1 |
| Winter Cover Crops in Context | 3 |
| Statistical and Process-Based Models to Evaluate Cover Crops | 5 |
| Dissertation Organization | 7 |
| References | 8 |
| CHAPTER 2. CORN YIELD RESPONSE TO WINTER COVER CROPS: AN UPDATED META-ANALYSIS | 12 |
| Abstract | 12 |
| Introduction | 13 |
| Materials and Methods | 18 |
| Results and Discussion | 25 |
| Summary and Conclusions | 46 |
| Acknowledgements | 47 |
| Appendix | 48 |
| References | 49 |
| CHAPTER 3. MAIZE SYSTEM IMPACTS OF COVER CROP MANAGEMENT DECISIONS IN IOWA: A SIMULATION ANALYSIS OF RYE BIOMASS RESPONSE TO PLANTING POPULATIONS | 57 |
| Abstract | 57 |
| Introduction | 58 |
| Materials and Methods | 61 |
| Results and Discussion | 68 |
| Conclusion | 77 |
| Acknowledgements | 78 |
| Tables and Figures | 79 |
| Appendices | 89 |
| References | 92 |
| CHAPTER 4. IMPROVED REPRESENTATION OF WINTER COVER CROPS: MODELING PHENOLOGY AND BIOMASS OF CEREAL RYE IN IOWA | 96 |
| Abstract | 96 |
| Introduction | 97 |
| Materials and Methods | 100 |
| Results and Discussion | 107 |

| | |
|------------------------------|-----|
| Conclusion | 116 |
| Figures and Tables | 117 |
| References | 129 |
| CHAPTER 5. CONCLUSIONS | 134 |

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ABSTRACT

Winter cover crops can be an effective strategy to buffer soil and water impairing effects from intensively managed agriculture. While cover crops have shown potential to sequester off-season nitrate, control weeds, or promote nutrient cycling, knowledge gaps persist in regard to maize impacts driven by cover crop decision making. In this context, statistical and process-based models can be valuable tools for predicting changes in maize systems that include a winter cover crop. In a meta-analysis combining peer-reviewed research from several regions in the US, grain yields were found to change between 0 and 21% when maize (*Zea mays* L.) followed a small cereal or a legume cover crop. In a second study, the APSIM model was calibrated to simulate a maize-rye (*Secale cereale* sp.)-rotation in Iowa, finding positive changes in maize system indicators – soil erosion, soil N-leaching, runoff, grain yields, and farm returns- in response to biomass gains from different rye populations. The third study combined field and statistical approaches to advance the rye simulation capabilities of the APSIM model. Using phenology records from two Iowa trials, we found different phyllochron (i.e. leaf appearance rate) between the late-fall and early-spring periods of active growth of a fall-seeded rye cover crop. Also, a global sensitivity analysis of a cover crop module embedded in APSIM revealed a high influence of thermal accumulation and soil water parameters to control phenology and biomass simulations. Overall, these studies revealed a positive contribution of winter cover crops to maize system performance, and it is expected that enhanced model representation of winter rye would facilitate future evaluations of cover crop effects at the field-scale level.

CHAPTER 1. GENERAL INTRODUCTION

Characterized by a current system that favors exports and large-scale production, US farms generate annual surpluses that ensure a steady domestic supply of food, fiber, and fuel. Further, several regions in the country benefit from rich and vast natural resources that inherently promote high-yielding agriculture and keep fueling the country's dominant role in world agricultural markets. In this context, the state of Iowa contributes greatly to the total agricultural output of the nation, receiving nearly 35 billion dollars in farm cash receipts, and ranking second country-wide as of 2018 (USDA-ERS, 2018). Thus, socio-economic forces and large utilization of fertile areas across the state have positioned intensively managed agriculture as the predominant production system, with maize and soybean emerging as the dominating crops.

Acreage devoted to maize has expanded dramatically in Iowa. Maize has an annual increasing rate of nearly 34,000 new hectares being planted each year, covering almost 50% of total cropland in the state (Iowa State University Extension and Outreach, 2018).

Technological advancements in farm machinery, farm practices, and genetic resources have contributed to escalating maize yields (Assefa et al., 2017), with many surpassing 200 bu. acre⁻¹ (i.e. 12,500 kg.ha⁻¹) in the most productive areas in Iowa. Yet, as much as this vibrant industry has grown and shaped the food system of the state and the nation, maize growers face current and future challenges. For one, farmers must increase farm output to levels that meet increasing world demand for food, fiber, and fuel; with the added challenge of minimizing its environmental footprints. Not surprisingly, maize production in the US-Midwest has been identified among the prime causes for soil and water quality deterioration in the Mississippi river basin and subsequent discharge of toxic sediments in the Gulf of

Mexico (Randall & Mulla, 2001). Challenges associated with reducing erosion rates or minimizing non-point contamination of watersheds while using farm inputs more effectively will become crucial under future weather and market instability.

Current national and state-level figures on soil degradation are discouraging. An unfair balance between conservation and direct-payment programs have stimulated grain production and has further worsened the problem (Cox, Hug, & Bruzelius, 1992). Annual soil loss rates of nearly 12 Mg. ha⁻¹ (~ 5 Tons.acre⁻¹) are allegedly considered “sustainable” for many soils and have been found to surpass or equate annual soil loss estimates ranging from 9.6 to 12.8 Mg. ha⁻¹ in Iowa. These estimations are nevertheless overly optimistic. Reports based on annual averages usually exclude gully erosion caused by extreme weather events, for which actual rates of detachment and deposition after a violent storm can be as high as 158 Mg. ha⁻¹ (Cruse et al., 2006).

Sustaining high yields, on the other hand, is highly demanding on soil resources. Since the radical transformation of Iowa’s original landscape, natural soil processes have been disrupted by highly extractive summer crops relying on synthetic fertilizer, contrary to the nutrient cycling that characterizes diverse native plant communities. In fact, nitrogen fertilizer use in Iowa has increased from 1 million to 10 million Tons from the 1960s to the mid-2000s whereas legume-associated rotations or manure applications have declined since then (Keeney & Hatfield, 2008). In turn, nitrogen use efficiency (NUE) has remained relatively low. Approximately 40 kg.N. ha⁻¹ are, on average, reportedly recovered for every 100 kg. N applied in maize-based rotations in the north-central US while the remaining 60% remains in the soil or is lost through different pathways, downgrading air and water quality as a result (Cassman, Dobermann, & Walters, 2002).

Water is also a major input for high yielding agriculture. Crop water consumption in Iowa and the upper corn-belt region is lower compared to arid or semi-arid areas, i.e. -200 mm on average (Basso & Ritchie, 2018). However, there is uncertainty in rain-fed producing areas about future water supply in response to climate driven variability. Extreme rainfall or drought episodes, for example, are expected to occur more erratically along the growing season, and moisture related stresses during critical periods, such as crop emergence or grain-filling, would ultimately reduce maize yields (Abendroth, 2014). Moreover, soil water not fully taken up by the crop is likely to deep-drain or run off the field, removing sediment, nutrients, and pollutants on its ways to nearby waterways (Dietzel et al., 2016).

Practices that empower growers to adapt to current and future challenges are needed. Negative impacts from otherwise highly-productive maize agricultural systems can be effectively reduced by increasing awareness among farmers, but most importantly, by integrating sound principles of soil conservation and sustainable production. Planting winter cover crops is one of these practices.

Winter Cover Crops in Context

Cover crops can help offset soil and water detrimental effects derived from maize production. Although cover crops are species with potential to: sequester N off-season (Poffenbarger et al., 2015), control summer weeds in conventional and organic systems (Mirsky, Curran, Mortensen, Ryan, & Shumway, 2011) and promote nutrient cycling while posing low risks to reduce main crop yields (Snapp et al., 2005); growers do not materialize direct economic returns from planting a cover crop (Bergtold, Ramsey, Maddy, & Williams, 2017). Farmers may eventually take advantage of a winter cover crop by harvesting its

biomass, yet the costs associated with such operations alongside founded, or unfounded, risk perceptions about the practice, contributes to the current barriers for adopting cover crops.

Winter cover crops are used sparsely, but there is expectation for future shifts in adoption. The agricultural census in 2012 estimated that 4 million hectares in the United States (~ 10 million acres) were planted to winter cover crops, and if current trends continue, total cover crop acreage in the country would increase to 8 million hectares (~ 20 million acres) by 2020 (Myers & Watts, 2015). Official data for Iowa is scarce, but a recent report from the Environmental Working Group (EWG) and Practical Farmers of Iowa (PFI) estimate that only 600,000 acres were planted to cover crops in 2016, which accounts for less than 3% of the total maize and soybean acres in the state (Rundquist & Carlson, 2017). Rundquist and Carlson (2017) also suggest that almost 30 years would be needed to reach cover crop goals of 12 million acres at the current adoption rates. Agronomic challenges and a lack of economic incentives seem to explain why cover crop adoption rates, though promissory, remain low. For example, Singer, Nusser, & Alf (2007) and Arbuckle & Roesch-McNally (2015) showed that growers who perceive tangible benefits and diversify their operations are more likely to adopt cover crops but also warn about management and economics gaps, which should be addressed first when planning initiatives to encourage farmers to use cover crops.

Research plays an important role in filling knowledge gaps as well as determining the value of cover crops for growers and policy makers. Some field evaluations, for example, have focused on managing planting and termination dates so that cover crop benefits are retained and subsequent maize yields are not penalized. (Hayden, Ngouajio, & Brainard, 2014; Lawson, Cogger, Bary, & Fortuna, 2015; Parr, Grossman, Reberg-Horton, Brinton, &

Crozier, 2011). Planting methods, such as broadcasting or interseeding, have also received increasing attention by farmers wanting to plant ahead of maize harvest and extend the limited growing season that challenges cover crop establishment in more northerly temperate areas (Brennan & Leap, 2014; Fisher, Momen, & Kratochvil, 2011; Wilson, Baker, & Allan, 2013). Surprisingly, limited research exists in regard to agronomic and economically driven evaluations of cover crop seeding rates (i.e. plant populations), which should be addressed considering that cover crop seed is the primary cost of the practice.

Overall, analyzing maize system performance driven by cover crop decision making is complex. Cover crop effects are site-specific for the most part, and single field studies do not provide easily scalable results. Therefore, models can be valuable tools to quantify the effects of diverse management strategies of a cover crop adapted to conventional maize rotations in Iowa and other areas in the Upper Corn Belt.

Statistical and Process-Based Models to Evaluate Cover Crops

Statistical tools can be highly effective in exploring factors related to potential benefits of a cover crop system. Models calibrated against field data from multiple years and sites have been used to inform management decisions of a cover crop system, for example, delineating growing-degree day (GDD) areas for optimal planting in the North-Atlantic region (Hashemi, Farsad, Sadeghpour, Weis, & Herbert, 2013) or coupling field data to biochemical models to predict maize yield responses to N supply of decomposing cover crops (White, Finney, Kemanian, & Kaye, 2016). Also, several quantitative reviews of the literature, or meta-analyses, have combined independent research and estimated overall maize responses to winter cover crops (Basche, Miguez, Kaspar, & Castellano, 2014; Marcillo & Miguez, 2017; Miguez & Bollero, 2005; Tonitto, David, & Drinkwater, 2006).

Meta-analysis is a robust exploratory technique because a mean response is estimated while specific errors with regard to site, year, or treatment variation (i.e. within and between-studies variances), are explicitly accounted for and quantified.

Process-based models extend the capabilities of statistically-driven models by linking clear physiological principles to soil and weather processes to predict different crop outcomes (Michael, Noah, Thomas, David, & Wolfram, 2017). Using process-based principles, cover crops have been traditionally modeled with species-specific designed tools or by adapting them into more general agronomic decision systems.

Species-specific models base their internal structures by narrowing the whole suite of benefits of a cover crop down to a single attribute of interest. For example, Tixier et al. (2011) created a model to select cover crop species that reduce weeds without decreasing N supply in banana crops and Qi et al. (2000) designed a model to predict flowering occurrence of legume cover crops grown to control erosion on hillside tropical fields. Also, simulation models have been developed to explore the applicability of winter rye (*Secale cereale sp.*) as an N catch crop or as a potential biomass source for the biofuel industry in the United States (Baker & Griffis, 2009; Feyereisen, et al., 2006) .

Agronomic simulation systems involve principles of growth and development that are generally applicable to multiple species. As such, time and effort spent in creating species-specific models can be saved by adapting more general modeling frameworks to simulate maize-based rotations that include a winter cover crop (Basche et al., 2016; Dietzel et al., 2016; Martinez-Feria, Dietzel, Liebman, Helmers, & Archontoulis, 2016). To enhance the applicability of these tools, however, crop models must be adjusted so that physiological responses of winter annual species adapted as cover crops reflect actual conditions of a

temperate region. Phenology of a winter annual cover crop, for example, is likely to respond differently to the progressive reduction in air temperatures that follow planting in the fall. Also, the separation between vegetative and reproductive phases in winter annual species is determined by environmental responses to variables other than temperature, such as, sensitivity to daylength, or the accumulation of cold requirements before flowering (i.e. vernalization). Likewise, successful establishment is a recurrent challenge among maize growers who integrate cover crops in their operations. Models that include management decision rules (e.g. plant populations, cover crop planting, cover crop termination, etc.) capture agronomic responses linked to net primary production (i.e. biomass), and as such, they allow for a more thorough evaluation of cover crop impacts on subsequent soil and yield processes.

Dissertation Organization

The overall objective of this research is to advance the scientific understanding of maize productivity impacts driven by cover crop utilization. Combining statistical and process-based models, this dissertation is divided into four chapters that span national, regional, and local levels of analysis. The first chapter presents a general overview of winter cover crops in the context of maize production in the US. The second chapter is a meta-analysis that summarized 50 years of peer-reviewed research in the United States and estimated the overall contribution of winter cover crops to maize yields across different regions and management conditions. In the third chapter, I ran agronomic simulations to quantify several production and economic indicators of a maize system (i.e. grain yields, soil erosion, runoff, N-leaching, and farm returns) in response to changing plant populations of a rye cover crop. The fourth chapter focuses on the value of enhanced characterization of small

grains (winter rye, [*Secale cereale* sp.]) in a process-based model used to simulate winter cover crops at the field-scale level. Additionally, I extended the capabilities of the APSIM model to simulate winter rye, reducing uncertainty in biomass predictions through robust methods of model sensitivity and parameter calibration. A final chapter gathers conclusions and final remarks of this research.

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CHAPTER 2. CORN YIELD RESPONSE TO WINTER COVER CROPS: AN UPDATED META-ANALYSIS

Modified from a manuscript published in the *Journal of Soil and Water Conservation*

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Abstract

Winter cover crops (WCCs) provide agronomic and environmental benefits, although their impacts on subsequent crop yields have been reported to vary across regions, soils, or under different farm practices. To address the variability in response, previous qualitative and quantitative reviews have summarized the overall yield effects of WCCs. However, the results from such reviews need constant revision as new research is published and interest in the conservation benefits of WCCs increases. Here, we update a previous meta-analysis of WCC effects on corn (*Zea mays*) yields, which summarized peer-reviewed research from the United States and Canada that was published between 1965 and 2004. Our updated data set (1965 to 2015) comprises 268 observations from 65 studies conducted in different regions of the United States and Canada, and includes information about the management practices utilized (i.e., WCC species, nitrogen [N] fertilization, termination date, tillage, etc.). The effect-size was the response ratio (RR), defined as corn yield following WCCs relative to yield after no cover crop (NC). As in the previous meta-analysis, our results showed a neutral to positive contribution of WCCs to corn yields. On average, grass WCCs neither increased nor decreased corn yields, although corn grown for grain yielded relatively higher than silage corn after grass WCCs. Legume WCCs resulted in subsequent higher corn yields by 30% to

33% when N fertilizer rates were low or the tillage system shifted from conventional tillage (CT) to no-tillage (NT). Mixture WCCs increased corn yields by 30% when the cover crop was late terminated (zero to six days before subsequent corn). Evidence of 65 years of research showed that uncertainty around the RR has decreased and corn yield response to WCCs has stabilized over time. Our results suggest that benefits of WCCs do not result in reduced corn productivity if properly managed.

Key words: corn-cover crops-meta- analysis- sustainable production

Introduction

Winter cover crops (WCCs) can improve soil health and provide benefits to subsequent cash crops. WCCs have been shown to effectively prevent soil erosion (Kaspar et al. 2001), reduce nutrient concentration and polluting loads in drainage waters (Kladivko et al. 2014), prevent nutrient leaching (Dabney et al. 2001), and increase soil carbon (C) inputs (Moore et al. 2014). Cumulative benefits of WCCs contribute to enhancing soil and water quality over time, but benefits beyond soil and water conservation, such as increased biological diversity, have been also quantified (Tillman et al. 2004). Winter cover crop adoption has risen (Dunn et al. 2016) in the midst of pressing demands to improve the sustainability of current cropping systems. For instance, initiatives such as the nutrient reduction strategy by the 12 states along the Mississippi River have recommended WCCs among other practices to reduce surface water contamination from nonpoint sources (INRS 2016). However, as WCCs are grown between cash (or summer) crops, there is a growing interest in understanding the agronomic repercussions of WCCs on crop production. Farmers recognize the value of WCCs in protecting the soil and the environment, but research has shown that persisting knowledge gaps about costs and management and concerns about subsequent yields limit

more extensive farmer adoption (Singer et al. 2007). Yield uncertainty is further complicated because WCCs respond differently across regions, soils, climates, and management practices; hence, cash crop response to WCCs can vary significantly.

WCCs can positively influence crop yields as a result of soil water conservation, nitrogen (N) supply, and weed suppression effects. WCC aboveground biomass can reduce soil water losses to evaporation or run-off (Clark et al. 1997; Truman et al. 2003), and WCC root biomass has been shown to improve soil aggregation, pore size distribution, and plant available water (Villamil et al. 2006). In addition, WCCs may contribute additional N to the subsequent cash crop and reduce fertilizer application requirements. Legume WCCs, for example, fix atmospheric N₂ and store organically rich N, which is decomposed by microbial activity and released in plant available form to the next cash crop. Yield increases due to greater biomass and N production of legume WCCs have been documented (Reeves 1994; Blanco-Canqui et al. 2015), although the magnitude of N supplied varies among studies because residue decomposition and posterior N release is highly dependent on climatic conditions and management (Frye et al. 1988). Finally, WCCs may be used to effectively control weeds. When intercropped with corn (*Zea mays*), the living mulch created by surface cover has provided weed control without the use of herbicides or mechanical tillage (Hartwig and Ammon 2002). Aside from outcompeting growing weeds for light and soil resources, effective rates of weed suppression have been documented also for control of new weeds due to allelochemicals, i.e., chemical compounds that hinder seed germination (Teasdale and Mohler 2000). Despite the positive benefits that WCCs can provide to a cropping system, several disadvantages have also been reported.

WCCs can adversely affect crop yields, although the mechanisms explaining this occurrence are more uncertain. While it is clear that WCCs and main crops compete directly or indirectly for resources, the mechanisms that explain yield penalties are not always consistent. Reduced cash crop populations, soil N immobilization, and soil water depletion have been proposed to explain yield reductions in subsequent crops. WCCs might lead to a reduction of cash crop populations because of interference between cover crop residue and farm equipment, which creates an incomplete seed furrow and impedes adequate seed to soil contact (Eckert 2013; Kaspar and Bakker 2015). Also, lower crop populations have been associated with slow emergence due to lower soil temperatures and seedling inhibition by allelochemicals released by WCC residues (Balkcom et al. 2007).

Another detrimental effect of WCCs is reduced inorganic N availability because of direct uptake during WCC active growth or N immobilization during residue decomposition (Waggoner and Mengel 1993; Kaspar and Bakker 2015). Low quality residue and insufficient biomass accumulation might lead to incomplete release of N to the next crop, decreasing yields unless N is supplemented (Blanco-Canqui et al. 2015; Dabney et al. 2001; Reeves 1994).

Finally, WCCs may reduce soil water storage, depleting reserves and negatively affecting yields of subsequent crops. Years with below normal precipitation (Munawar et al. 1990), coarse drought-prone soils, or soils insufficiently recharged prior to main crop early growth, may worsen water depletion linked to reduced crop yields (Reeves 1994).

As cover crops may result in positive or negative effects on yield, discrepancies arise in regard to their overall contribution to a cropping system.

Several systematic reviews have been conducted to analyze the overall effect of WCCs, factoring in environment and management conditions driving the variability in response. For example, Unger and Vigil (1998) analyzed cover crop effects in relation to water use across regions, concluding that WCC effects are mostly positive in humid and sub-humid areas and provide additional nutrient cycling benefits compared to other water conserving practices alone, such as conservation tillage. Blanco-Canqui et al. (2015) found overall positive yield influences in a summary of WCC research from temperate soils, and Fageria et al. (2005) concluded in their review that proper WCC management contributes to improving main crop yields and soil water quality. Likewise, by reviewing promising WCC species across different regions, Snapp et al. (2005) pointed out overall benefits as long as farmers set specific goals for their operations.

Most reviews have systematically compiled the literature around WCCs in relation to crop yields, yet only a few have included a statistical treatment or meta-analysis of the data sets derived from the literature review (Valkama et al. 2015; Sileshi et al. 2008; Tonitto et al. 2006; Miguez and Bollero 2005).

Meta-analysis methods have been applied to analyze agronomic performance, allowing for the combination of independent research to address specific hypotheses. The techniques of meta-analysis ensure a proper selection of studies, synthesis of results, and control of bias resulting from missing representative studies on a topic (Pai et al. 2004). Meta-analysis also offers statistical advantages in agricultural research. By pooling observations from several studies, meta-analysis extends the low statistical power associated with single studies (e.g., decreasing the likelihood of noting an absence of differences when there are in fact significant effects [Arnqvist and Wooster 1995]). Further, meta-analysis allows

researchers to discriminate the variation due to experimental or management conditions between studies, and model it explicitly (Kiær et al. 2009).

Updating meta-analysis studies is routinely done in the medical and social sciences, but it has rarely been conducted in agriculture. Failing to update a meta-analysis can result in holding results as fixed without considering recent methodological advances, or simply, the accumulation of new evidence on a major research topic since its publication.

The meta-analysis by Miguez and Bollero (2005) provided insight about the influence of WCCs on corn production. By reviewing 40 years of WCC research in the United States and Canada, WCCs were shown to provide neutral to 21% increase in corn yields across different regions and management conditions. Despite these results, there are agronomic and methodological reasons that motivate an update of this review. WCCs are arguably even more relevant today as current and new users call for better management practices to maximize conservation benefits while reducing economic risk from their farm investments.

Interest in cover crops has expanded along with the need for management and technical information about their use since the release of the nutrient reduction strategies (INRS 2016) within the Midwest (ILF 2015). Also, WCC research since the first meta-analysis has continued, and studies that investigate a variety of topics, such as species selection, crop yield effects, nutrient leaching, and erosion control are continually being published.

As more research is accumulated on a topic, specialists recommend including new references and updating a meta-analysis so conclusions from the previous work may be revised (Moher et al. 2008; O'Connor et al. 2008). Among the few examples in agriculture, expanding the number of publications, and in some cases revisiting the structure of the

supporting data sets, has resulted in a major shift of the conclusions from previous meta-analyses, such as the case of organic versus conventional yields (Badgley et al. 2007; Seufert et al. 2012; Ponisio et al. 2015). In addition, updating a meta-analysis does not only involve including additional observations from the most recent literature, but can also consider changes or improvement in methods for increased robustness of the results (O'Connor et al. 2008). For instance, in reviewing worldwide crop yield responses to climate change, Challinor et al. (2014) updated a previous meta-analysis (IPCC 2007) and introduced more robust methods to capture yield responses to warming conditions not detected before. Therefore, a fresher outlook to analyze WCC contribution to corn yields is needed, along with an assessment of the conditions by which WCC contribution differs across different regions, in light of the evidence of the last 10 years of research.

For this updated meta-analysis, we maintain the same methods and research questions from Miguez and Bollero (2005). Including information about the cropping system, we update the overall corn yield response to WCCs based on peer-reviewed publications from the last 10 years (2005 to 2015). Specifically, our objectives were to (1) estimate mean corn yields comparing systems with and without WCCs, (2) assess variability in corn yield response to WCCs affected by management conditions (e.g., N fertilization, WCC species, WCC planting and termination dates, tillage, etc.), and (3) assess temporal changes in corn yield response to WCCs depending on evidence accumulated over time.

Materials and Methods

Database Preparation. Following the criteria outlined by Miguez and Bollero (2005), we updated a previous database of 37 peer-reviewed publications, which included studies from 1965 to 2004. We used Institute for Scientific Information (ISI) Web of Science (Thomson Reuters, New York, New York) and Google scholar (Google Inc., Mountain

View, California) to search for studies in the 2004 to 2015 period that matched the following Boolean expressions: “Corn yield *and* winter cover crops *or* cover crops.” Furthermore, studies included in the database had to meet all the following criteria:

1. Yield records came from corn following a cover crop treatment, and corn following no cover (NC).
2. Yields were reported in more than one year or location.
3. Enough information was provided to compute study variances.
4. The studies were conducted in the United States or Canada.

Table 1. Moderators of corn yield response to winter cover crops (WCC) included in the updated meta-analysis, 1965 to 2015.

| Variable | Description for factors and mean and range for continuous variables |
|--|--|
| Tillage (n=268) | Conventional, no-till |
| WCC species (n=268) | Grass, legume, and mixture. |
| Region (n=268) | Southeast, Northeast, Canada, North Central, Great Plains, Southwest, Northwest. |
| Corn yield (n=268) | Grain, Biomass |
| NFR, Nitrogen fertilizer rate (Kg. ha ⁻¹) (n=268) | Low: 0-99, mid: 100-199, high: >200) |
| WCC termination (days before corn) (n=215) | 15 (0-35) |
| WCC seeding period (n=248) | Early: before corn harvest, Late: after corn harvest. |
| Soil texture (n=238) | Very fine, fine, medium, medium fine, coarse |

| | |
|--|---------------|
| WCC growth season (Julian days) (n=207) | 250 (60-300) |
| WCC biomass (Mg. ha ⁻¹) (n=194) | 1.2 (0.6-3.0) |

In addition to the original 37 publications, 28 articles out of 395 were recovered in this fashion (table A1, appendix). Thus, the updated database comprises 65 articles with publication range between 1965 and 2015. From the total, 58 studies were conducted in the United States and 7 in Canada. Following standard meta-analysis methods, we included factors in the database with potential to moderate WCC effects on corn yields. Factors refer to conditions of the cropping system employed in a study, such as tillage, WCC species, region, corn yield, N fertilizer rate (NFR), and WCC termination date.

An additional variable, which indicates the type of corn yield (as a categorical variable), was included to describe whether yields of the following crop were reported for grain or biomass for silage. For ease of comparison, we set the levels of each factor at those defined previously by Miguez and Bollero (2005). Additionally, we analyzed the following factors not included in the previous meta-analysis: WCC seeding period, soil texture, WCC growing season, and WCC biomass. Seeding period included two levels: (1) late seeding for WCCs drilled or broadcasted after corn harvest, and (2) early seeding for WCCs interseeded at late stages of standing corn. To reduce soil textural classification to a manageable number, we defined the following five categories of soil texture (Wösten et al. 1999): very fine, fine, medium, medium fine, and coarse. WCC growing season refers to Julian days elapsed between the average seeding and average termination dates reported in a study. Biomass accounts for aboveground WCC dry matter recorded at, or near, termination of the cover

crop. Table 1 displays a full description of the moderators of yield response to WCCs, distinguishing between continuous and categorical, and including number of observations for the two-time periods in the meta-analysis.

Data Analysis. The dependent variable indicates the efficacy of a cover crop treatment relative to NC control (i.e., effect size for a study), and was quantified as a response ratio (RR). RRs have been used to evaluate cover crop performance under different scenarios (Miguez and Bollero 2005; Kuo and Jellum 2000; Olson et al. 1986). RR for a study is calculated by dividing corn yield following a WCC treatment to corn yield following NC:

$$RR = \frac{Yield_{wcc}}{Yield_{nc}} \quad [1]$$

Depending on the experimental layout, a cover crop treatment in combination with another factor produced multiple RRs for a study. For instance, WCC species and N combined in a factorial arrangement resulted in an RR for each species calculated at each application rate. Finally, RRs were log-transformed to normalize the data and ensure that changes in numerators and denominators were affected equally (Borenstein et al. 2010; Basche et al. 2014).

Variability due to differences within and between studies was assessed following the methods by Borenstein et al. (2010). Standard deviations (SD), yields (Y), and sample sizes (n) for WCC and NC treatments were used to estimate within-study variances:

$$v_i = \frac{SD_{wcc}^2}{n_{wcc} * Y_{wcc}^2} + \frac{SD_{nc}^2}{n_{nc} * Y_{nc}^2} \quad [2]$$

Within-study variances of 55 studies were determined following such an approach. One study (Singer et al. 2008) reported neither SD nor n , yet the authors provided their original data sets upon request. The two remaining studies (Bundy and Andraski 2005; Crandall et al. 2005) provided either one or all of the following statistics: least significant differences (LSD), standard error of the mean (SE), coefficient of variation (CV), or 95% confidence intervals (CI), from which standard deviations and within-study variances were recovered. On the other hand, between-studies variance (σ^2_b) quantifies true differences in corn yield response across WCC studies (i.e., non-sampling error related), and was estimated following a weighting approach to correct for unequal within-study variances (Borenstein et al. 2010).

Homogeneity in the distribution of log-RR (i.e., null hypothesis that WCC had similar effects on corn yield across studies) was tested by computing total variance, or weighted total sum of squares for log-RR (Q-statistic). Weights in the calculation of Q equaled to the inverse of within-study variances (Viechtbauer 2010). The Q-statistic follows a chi-square distribution with $(n - 1)$ degrees of freedom; therefore, a Q estimate whose p -value is less than 0.05 led to reject the null hypothesis and conclude that studies did not share a common effect size (i.e., WCC effects differed across studies). Further, we used the I-square (I²) index to determine the presence of heterogeneity in our data set.

Such an index reflects the proportion of observed variability indicated by between-study variance, or the heterogeneity in WCC effects arising from reasons other than sampling error or year/location effects. The I-square index is computed by dividing the difference

between total variance (Q) and its degrees of freedom ($n - 1$) by total variance itself (Huedo-Medina et al. 2006). I^2 values above 25% or 50% suggest a significant amount of heterogeneity, for which additional techniques, such as subgroup homogeneity analysis or meta-regression, can be used to explore additional reasons for such heterogeneity in response. (Higgins and Thompson 2002).

Evidence of heterogeneity in log-RR allowed for the inclusion of moderators that explained the significant variance between studies. As such, we partitioned total variance (Q) into between-group components for each factor moderating WCC response in table 1 and tested whether they were significant if $p < \alpha$ (0.05). For the significant moderators, a subgroup analysis of homogeneity was conducted, further partitioning variance into within-group components (i.e., levels within such significant factors), and using $\alpha = 0.01$ to protect against Type I errors (i.e., falsely reject a true null hypothesis). Finally, weighted mean log-RR and 95% CI were estimated using weights equal to the reciprocal of total variance (i.e., within-study variance computed with equation 2 plus between-studies variance estimated in the homogeneity analysis):

$$\log(RR) = \frac{\sum_{i=1}^n \frac{1}{(v_i + \sigma_b^2)} \log(RR_i)}{\sum_{i=1}^n \frac{1}{(v_i + \sigma_b^2)}} [3]$$

For ease of interpretation, weighted mean log-RRs were back transformed to ratio form by applying anti-logs.

Sensitivity Analysis and Publication Bias. We conducted a sensitivity analysis to detect temporal changes in corn yield response to WCCs given the evidence of 50 years of research in the United States and Canada. A cumulative random effects meta-analysis (CMA) without moderators, following Viechtbauer (2015) and Leimu and Koricheva (2004), was conducted to estimate weighted mean effect size while controlling for publication year of the studies in the database. In the CMA, after the earliest available study was entered, observations were sorted in chronological order, pooled by publication year, and added one year at a time. Observations pertaining to studies published in the same year were randomly allocated. Then, yearly weighted mean log-RR and 95% CIs were recalculated following the same estimation procedures for mean effect size in the homogeneity analysis (equation 3). In other words, the CMA tested significant differences of WCC effects and estimated mean yield response at every available publication year between 1965 and 2015 (i.e., indication of time trends of WCC driven variability in corn yields or how evidence in WCC effects have evolved over time).

To investigate publication bias in the data set, we used funnel plots of effect size (log-RR) against the inverse of standard error. Because such plots indicate how effect size and study precision are related, a symmetric funnel shape in the scattering of individual observations is expected, with increasing scatter for less precise studies. Asymmetric funnels usually depict a relationship between effect size and precision, which may suggest indication of small studies failing to report nonsignificant results, suppression of data relevant to the meta-analysis, etc. (i.e., publication bias) (Anzuers-Cabrera and Higgins 2010).

Meta-Regression. To account for additional reasons that explain between-study variability, we explored the quantitative relationship between corn yields and WCCs by

including management factors of the cropping system. Meta-regression models have been applied to capture differences between studies that explained variability of grain yield responses to trial variety mixtures (Kiaer et al. 2009), grain yield responses to catch crops affected by fertilization rates (Valkama et al. 2015), or crop yield responses to tillage affected by crop rotation and degree of tillage intensity (Van den Putte et al. 2010). In the meta-regression model, the dependent variable was log-RR, and was regressed against the continuous variables N fertilization and WCC termination. Mixed models with interactions were fitted, incorporating effects at the study level (St-Pierre 2001), and including the fixed effect factor WCC species along with random terms for the slopes and intercepts of each study in the database. Weighted models, robust to compensate for the unequal variance effect (Khoshravesht et al. 2015), were fitted for N fertilization and WCC termination. The models were run separately because of unequal number of observations and to avoid overparameterization in a full model.

The meta-analysis (homogeneity analysis, subgroup analysis, mean effect size estimation, funnel plotting, and sensitivity analysis) was conducted through functions available in the metafor R-package, version 1.9-8 (Vietchbauer 2015). To fit the mixed effects model and estimate parameters for the meta-regression, we used the R-package linear mixed-effects (lme4), version 1.2 (Bates et al. 2015).

Results and Discussion

We found evidence of heterogeneity in our cover crop database (table 2). The previous meta-analysis (Miguez and Bollero 2005) reviewed cover crop effects reported by 37 publications, finding a large between-studies variability (i.e., $I^2 = 59\%$) in 160 observations. In this updated meta-analysis, the sample size increased by 67.5%, including observations

from 28 additional publications, resulting in a higher and significant sum of squares ($Q = 706$, $n = 268$, and $p < 0.001$; table 2).

Between-studies variance for the previous and the updated meta-analyses was estimated at 0.007 and 0.008, respectively, which confirmed the presence of more systematic causes for the variation in yield response to WCCs (i.e., $I^2 = 62\%$). In exploring the factors that moderated yield response to WCCs (table 3), we found significant effects of WCC species, region, and NFR, as previously reported by Miguez and Bollero (2005). Additionally, we found significance for WCC termination (i.e., days before subsequent corn) in the updated meta-analysis.

Because WCC species accounted for much of the variability, we repeated the homogeneity analysis at the following three levels of this category: grass, legume, and mixture WCCs.

Winter cover crop species We found significant differences in yield response for the three WCC groups (table 4), and not only for the legume subgroup as in Miguez and Bollero (2005). Variability partition, evaluated through homogeneity analysis at each level of WCC species (table 5), revealed different moderators of yield response for grass, legume, and mixture WCCs.

Mixtures The weighted mean response for the mixture group was 1.13, with a 95% CI not including 1, which means that corn following a mixture WCC treatment showed 13% higher average yields than NC (figure 1). While this estimation is lower relative to the previous meta-analysis (21.5%; Miguez and Bollero 2005), the CI has also narrowed due to the larger sample size for the update (i.e., $n = 10$ and $n = 28$ for the first and the updated meta-analysis, respectively).

Table 2. Homogeneity of corn yield response to winter cover crops (WCC). Total sum of squares (Q), between-study variance(σ_b^2), heterogeneity (I^2), and number of observations for two periods of analysis.

| Period | Q | σ_b^2 | I^2 | Studies | Observations (n) |
|-----------|------------|--------------|-------|---------|------------------|
| 1965-2004 | 386 (.001) | 0.007 | 58.81 | 37 | 160 |
| 2005-2015 | 300 (.001) | 0.008 | 64.32 | 28 | 108 |
| 1965-2015 | 706 (.001) | 0.008 | 62.18 | 65 | 268 |

Values between parentheses denote significance at $p < 0.05$

$$I^2 = \frac{Q - (n - 1)}{Q} \times 100$$

Previous research has attributed corn yield benefits of mixture WCCs to greater biomass production, which reduces soil erosion and improves weed control (Kuo and Jellum 2002).

Further, biomass production of cover crop mixtures has been reported as highly dependent on termination date (Clark et al. 1997) as it affects composition and quality of the cover crop residue (Ruffo and Bollero 2003). By including additional observations for mixture WCCs, we were able to detect significant differences for biomass and termination date not reported before (Miguez and Bollero 2005). Mixture WCC observations were not homogeneous ($Q = 92.00$, $n = 28$, $p < 0.001$; table 4). Between-studies variance was estimated at 0.015 and explained 70% of total variability (i.e., $I^2 = 70$). The homogeneity analysis for mixture WCCs showed significant effects for WCC termination and WCC biomass, suggesting that the two factors explained a considerable amount of variation in yield response ($p < 0.001$; table 5).

The homogeneity analysis for WCC termination within mixture showed that the RR increased as termination date decreased (figure 2). When a mixture WCC was terminated 14 or more days ahead of the subsequent corn crop, yields were lower but not significantly different than NC. Mid-termination did not exhibit differences either for corn following mixture WCCs or NC, yet the mean RR was above 1. On the contrary, mixture WCCs that were late terminated (i.e., zero to six days before subsequent corn) displayed a significant 30% increase in corn yield relative to NC. Late and mechanically terminated mixtures, as in Wortman et al. (2013), have been shown to result in higher corn grain yields in relation to NC (16% to 22%) because of increased biomass that reduced early-season weeds. Managing mixtures poses more challenges compared to a single species system, yet the higher seeding rates associated with them can lead to greater biomass production (Kuo and Jellum 2002). In turn, timely WCC termination accompanied by residue management practices maximize the benefits that double or multiple WCC systems can bring to subsequent cash crops, such as increased N availability through biological N₂ fixation and nutrient cycling (Kuo and Sainju 1998), increased N mineralization and crop uptake (Sainju and Singh 2001), and soil moisture conservation before main crop planting (Wortman et al. 2012).

Table 3. Homogeneity analysis for moderators of yield response to winter cover crops (WCC). Between-groups sum of squares (Q), p-values (p), and number of observations (n) for the updated meta-analysis (1965-2015).

| Moderator | Q | p | n |
|-------------|-------|---------|-----|
| Tillage | 0.00 | 0.970 | 268 |
| WCC species | 70.03 | <0.0001 | 268 |
| Region | 37.80 | <0.0001 | 268 |
| Corn yield | 0.68 | 0.411 | 268 |

| | | | |
|--------------------|-------|---------|-----|
| NFR | 35.98 | <0.0001 | 268 |
| WCC termination | 8.50 | 0.010 | 215 |
| WCC seeding period | 2.74 | 0.431 | 248 |
| Soil texture | 1.06 | 0.786 | 238 |
| WCC growth season | 0.04 | 0.827 | 207 |
| WCC biomass | 3.40 | 0.070 | 194 |

$p < 0.05$ indicates significant effects for a moderator of yield response to WCC

Grasses. Grass WCCs showed neutral effects on corn yields. The weighted mean response was 1 (0.98 to 1.02), which means that corn yields following a grass WCC were not significantly different than NC (figure 1). The weighted mean RR for grass WCCs remained relatively unchanged relative to the previous meta-analysis (0.99, $n = 70$), although the sample size has doubled, including 70 additional observations.

Most new observations came from small grain studies published during the 2005 to 2015 period in US northern regions and Canada. While corn yields neither increased nor decreased, grass WCC effects were not homogeneous, and hence, differed across studies ($Q = 203.8$, $n = 140$, $p < 0.0001$; table 4). Between-studies variance was estimated at 0.002 and accounted for 32% of total variability in grass observations (i.e., $I^2 = 32$). The homogeneity analysis for grass WCCs determined significant variation in response due to the corn yield variable ($p < 0.01$), suggesting different RRs to be estimated for grain and silage corn, respectively (table 5).

Table 4. Homogeneity analysis of corn yield response to winter cover crops (WCC). Sum of squares (Q), between-study variance (σ^2), heterogeneity (I^2), and number of observations for the three levels within WCC species.

| Species | Q | σ_b^2 | I^2 | Studies | Observations (n) |
|---------|------------|--------------|-------|---------|------------------|
| Grass | 203 (.001) | 0.002 | 31.87 | 47 | 140 |
| Legume | 352 (.001) | 0.016 | 71.63 | 36 | 101 |
| Mixture | 92 (.001) | 0.015 | 70.65 | 13 | 28 |

Values between parentheses denote significance at $p < 0.05$

$$I^2 = \frac{Q - (n - 1)}{Q} \times 100$$

From the homogeneity analysis for grass WCCs, it was determined that the RR increased when corn was harvested for grain, and decreased for silage corn (figure 3). When corn harvested for silage followed a grass WCC, yields were lower but not significantly different from NC. Corn harvested for grain yielded relatively higher than silage corn after grass WCCs, yet did not show significant differences with respect to NC. Although corn yields for the grass group were not significantly different from NC, differences in response for silage and grain systems may occur as the result of extended growing periods in silage production, or diminishing quantity and quality of ears produced in grain systems. Silage production, for example, allows for extended harvest periods when planting is delayed, but the risk of erosion and nitrate (NO_3^-) leaching increases due to the aggressive removal of residue, which may impact yields ultimately. In dairy cropping systems where grass WCCs help mitigate environmental impacts from silage production, Krueger et al. (2011) reported biomass yield penalties when rye (*Secale cereal* L.) WCC grew four extra weeks relative to early terminated rye; otherwise neutral in terms of its impacts to subsequent silage yields.

Also, the likelihood of silage yield penalties after grass WCCs might be reduced by selecting less winter-hardy species. For instance, Hashemi et al. (2013) reported 41% higher silage for corn that followed oats (*Avena sativa*) relative to NC, possibly due to winter-kill and increased time for decomposition and greater N release. In contrast, neutral grain yield effects have usually been associated with grass WCCs, although yield penalties may still occur.

Table 5. Subgroup homogeneity analysis. Sum of squares (Q), p-values(p), and number of observations (n) for the moderators of corn yield response within the three levels of winter cover crop (WCC) species.

| Species | | Tillage | Region | Corn yield | NFR | WCC termination | WCC seeding period | Soil texture | WCC growth season | WCC biomass |
|----------------|----------|---------|--------|------------|---------|-----------------|--------------------|--------------|-------------------|-------------|
| Mixture | Q | 3.004 | 4.275 | 0.0588 | 0.3836 | 39.65 | 1.112 | 3.340 | 1.204 | 9.671 |
| | p | 0.083 | 0.370 | 0.808 | 0.825 | <0.0001 | 0.573 | 0.060 | 0.273 | <0.001 |
| | n | 28 | 28 | 28 | 28 | 25 | 28 | 28 | 26 | 26 |
| Grass | Q | 4.491 | 7.374 | 6.157 | 0.504 | 0.033 | 2.263 | 3.213 | 2.414 | 3.156 |
| | p | 0.034 | 0.117 | 0.009 | 0.777 | 0.983 | 0.519 | 0.667 | 0.120 | 0.076 |
| | n | 139 | 139 | 140 | 139 | 109 | 126 | 125 | 109 | 102 |
| Legume | Q | 6.578 | 15.460 | 0.323 | 20.170 | 1.768 | 2.672 | 2.220 | 3.470 | 1.363 |
| | p | 0.0103 | 0.008 | 0.569 | <0.0001 | 0.413 | 0.445 | 0.695 | 0.062 | 0.243 |
| | n | 100 | 101 | 101 | 100 | 81 | 93 | 84 | 72 | 70 |

Note: 0.01 was used for protection against Type I errors. NFR= nitrogen fertilizer rate

To explain yield reductions, several hypotheses have been proposed, such as reduced corn populations and higher number of barren plants resulting from poor seed to soil contact due to interference of WCC residue and planters (Kaspar and Bakker 2015), reduced soil temperatures that slow emergence (Kaspar et al. 1990), or allelopathic effects inhibiting germination (Reberg-Horton et al. 2005).

Legumes. Legume WCCs showed overall positive effects on corn yields. The weighted mean response was 1.21 (1.17 to 1.29), which means that corn that followed a legume WCC yielded 21% more than without a cover (figure 1). The weighted mean RR for legume WCCs has also remained stable when compared to the previous meta-analysis (1.21, $n = 81$). Twenty new observations from six publications were included in the updated meta-analysis. The sample size for legume WCCs increased only 25%, but the major areas sampled in the first meta-analysis are still represented: Canada, the Southeast, and North Central regions of the United States.

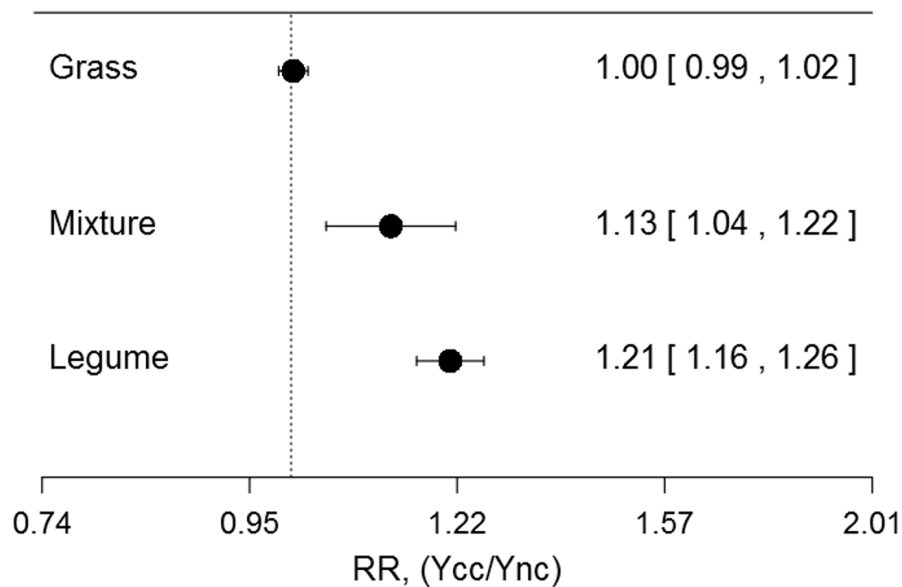


Figure 1. Mean response ratio (RR; yield of corn following winter cover crops/yield of corn following no cover [Ycc/Ync] and 95% confidence interval (horizontal bars) for three levels of winter cover crops.

The distribution of RR was significantly nonhomogeneous ($Q = 352.25$, $n = 101$, $p < 0.001$; table 4), and between-studies variance was 0.016. Differences between studies

accounted for 70% of total variation in yield response for legume observations ($I^2 = 70$). The homogeneity analysis for legume WCCs revealed significant effects for tillage, region, and NFR in moderating the yield response ($p = 0.01$ and $p < 0.01$, respectively; table 5). Because region was a significant moderator of differences overall (table 3), it is analyzed separately in the next section.

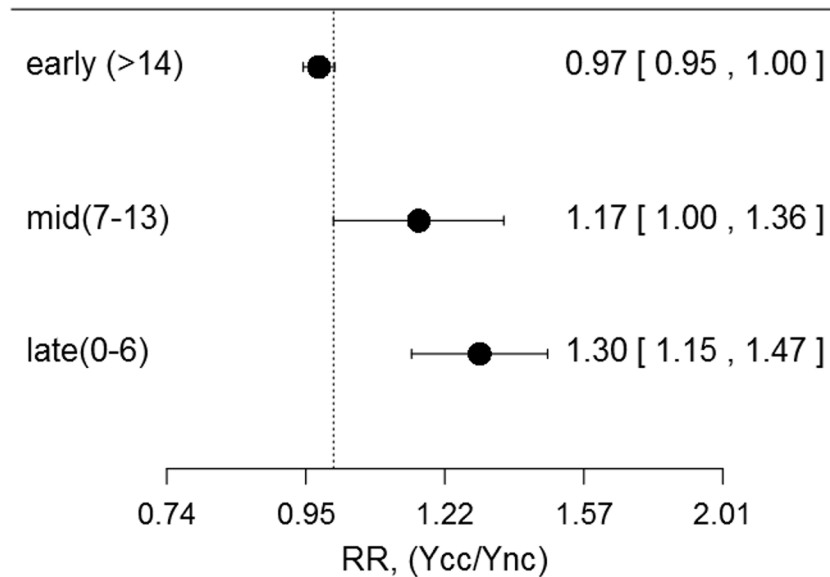


Figure 2. Mean response ratio [yield of corn following winter cover crops/yield of corn following no cover, (RR)] and 95% confidence interval (horizontal bars) for the three levels of termination date (days before corn) within mixture.

As evidenced by the homogeneity analysis for NFR within legume WCCs, the RR decreased with increasing NFR (figure 4). For low N rates (0 to 99 kg ha⁻¹ [0 to 88.3 lb ac⁻¹]), corn yields were significantly higher following a legume WCC than following NC. As N rates increased from 100 to 199 kg ha⁻¹ (89.2 to 177.5 lb ac⁻¹), yield increases following a

legume WCC were only 9%. Yields for legume WCCs and NC were not significantly different when N fertilizer was 200 kg ha⁻¹ (178.4 lb ac⁻¹) or higher.

These findings are similar to those reported by Miguez and Bollero (2005) and relate to lesser yield response at high NFR because of considerable N mineralization and N release following legume residue decomposition. Legumes symbiotically fix and supply significant amounts of N (Blanco-Canqui et al. 2015), providing rapid release of mineralized N when their residues, of good quality and C/N ratios of 20 or less, decompose (Dabney et al. 2001). Miguez and Bollero (2006) analyzed corn response to hairy vetch (*Vicia villosa*), finding higher yields relative to NC at low and high N rates, suggesting that legume WCC benefits result from improved soil N availability but can also extend beyond N supply.

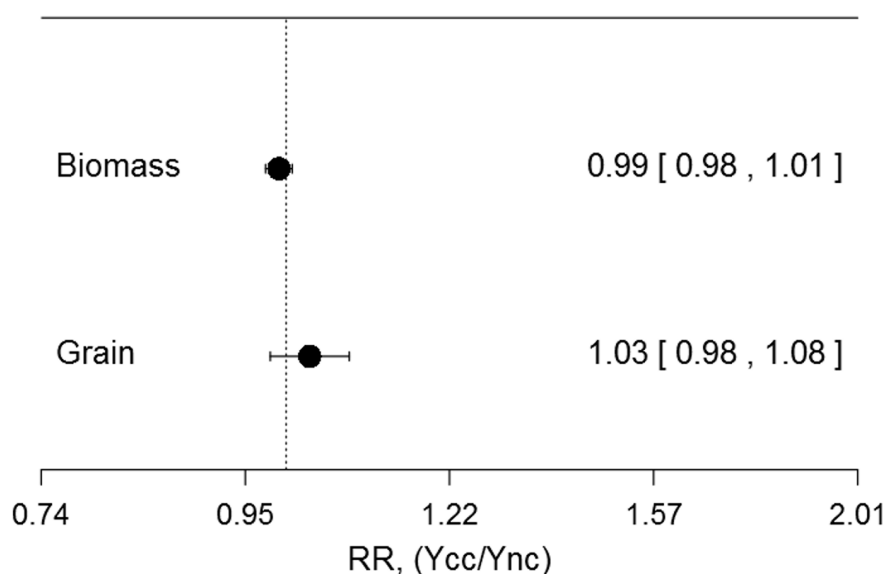


Figure 3. Mean response ratio [yield of corn following winter cover crops/yield of corn following no cover (RR)] and 95% confidence interval (horizontal bars) for the two levels of the corn yield variable within grass.

Legumes have been shown to provide non-N-related benefits even at considerably high fertilizer rates, such as reduced soil evaporation and increasing soil moisture savings in warmer climates (Clark et al. 1997). Furthermore, legume WCC benefits seem to accrue when more than a single species is used. For example, early season N was positively correlated with yield increases up to 2.6 Mg ha⁻¹ (1.16 tn ac⁻¹) for corn that followed more than one legume WCC (Smith et al. 2008), which could be explained through ecological mechanisms hypothesized for the over yielding capacity of non-N fixing species growing along with multiple legumes in unmanaged ecosystems.

The homogeneity analysis for legume showed also that the RR increased when tillage system changed from conventional to no-tillage (NT) (figure 5). Significant effects for tillage were not detected in the previous review (Miguez and Bollero 2005). Under CT, corn following legume WCCs exhibited yields 15% higher than NC. Conversely, the yield increase was 30% for NT corn following a legume WCC. WCC benefits are more rapidly realized in NT managed systems due to physical and chemical changes in the soil as a result of greater surface residue compared to CT (Blanco Canqui et al. 2015). Tillage breaks down soil aggregates and speeds up microbial decomposition of exposed residue, which in the case of legume WCCs can lead to rapid N mineralization and release when the soil is plowed (Balkcom et al. 2007). Subsequent lower corn yields under tillage systems may be the result of the asynchrony between N mineralization and the period of high N demand for the crop.

Region. The homogeneity test displayed significant differences in yield response to WCCs due to region (table 3). The North Central region of the United States experienced a seven-fold increase in sample size (i.e., 11 observations in the first meta-analysis) and 77 new observations in the update. The updated database included observations from Illinois

(14), Iowa (22), Wisconsin (17), Minnesota (2), and Michigan (12)—states not represented before.

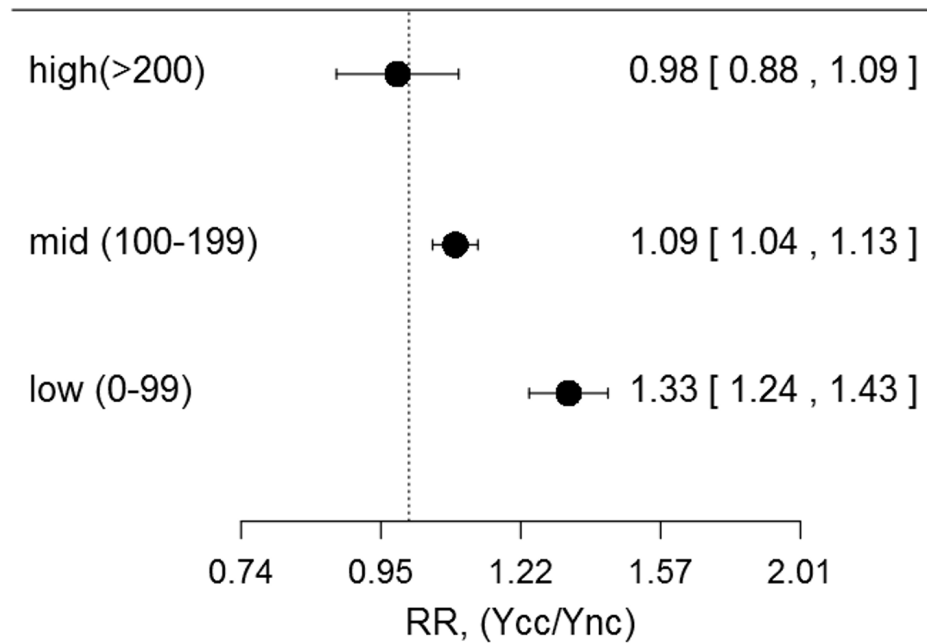


Figure 4. Mean response ratio [yield of corn following winter cover crops/yield of corn following no cover (RR)] and 95% confidence interval (horizontal bars) for the three levels of nitrogen fertilizer rate (NFR) within legume.

The Southeast region and Canada comprised nine new observations each, representing a 10% increase in sample size. The Great Plains, excluded from the analysis in Miguez and Bollero (2005) due to a single observation available, increased its sample size to six observations and hence was included for analysis. Neither the Northeast nor the Northwest presented new observations. Due to an overall larger data set, CI for weighted mean RR moderated by region diminished considerably.

The homogeneity analysis showed significant differences across regions (figure 6). The CI for weighted mean RR encompassed 1 for the Great Plains, Canada, and North Central regions. Thus, yield response to WCCs in these regions were not significantly different from NC. The lack of differences between corn with WCCs and NC is a consequence of the limited yield benefits expected from short growth seasons and severe winters in northern regions.

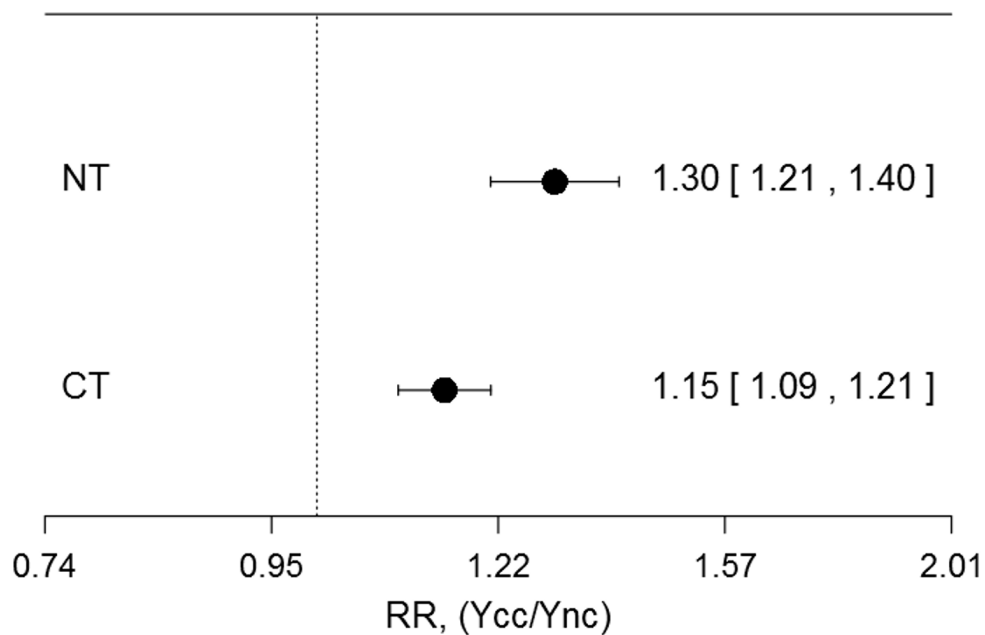


Figure 5. Mean response ratio [yield of corn following winter cover crops/yield of corn following no cover (RR)] and 95% confidence interval (horizontal bars) for the two levels of tillage within legume.

In view of these constraints, WCCs are likely grown for their benefits unrelated to yield. For instance, WCCs are grown to sequester out-of-season $\text{NO}_3\text{--N}$ and improve water quality, which is a high priority in Corn Belt states (Kladivko et al. 2014). In addition, challenging

establishment limits adoption of other species (Singer 2008), and overseeding winter-hardy small cereals into corn is sometimes the most viable option (Snapp et al. 2005).

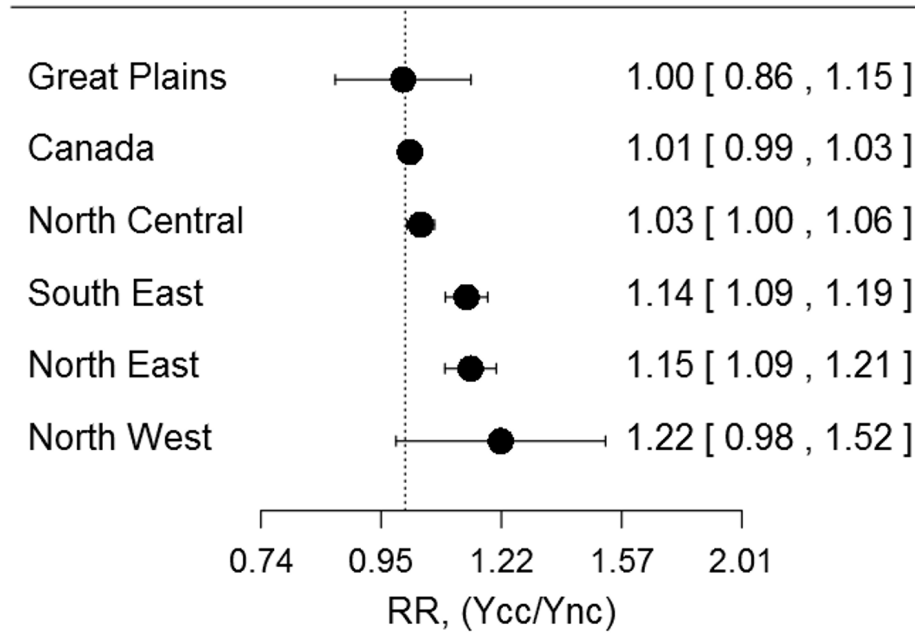


Figure 6. Mean response ratio [yield of corn following winter cover crops/yield of corn following no cover (RR)] and 95% confidence interval (horizontal bars) for the 6 levels of region.

It is not surprising that grass WCCs predominate in much of the North Central region, where yield benefits might be marginal, yet the environmental impact is considerable. On the other hand, Southeast and Northeast regions showed positive and significant effects of WCCs. Weighted mean RR for these regions were 1.12 and 1.14, respectively, with 95% CI not including 1. It follows that corn with WCCs yielded between 12% and 14% above NC. These findings are similar to those reported by Miguez and Bollero (2005). Southern warmer climates offer conditions for better establishment of heat tolerant species that grow rapidly, control weeds efficiently, and respond favorably to irrigation (Ngouajio and Mennan 2005; Snapp et al. 2005). WCCs alongside other conservation practices have been successfully implemented to restore eroded and coarse textured soils in humid southern regions without losing productivity (Sainju et al. 2002). Grasses and legumes have been successfully tested in

Alabama, where winter rye showed neutral effects in subsequent corn biomass yields (Mourtzinis et al. 2015), whereas dense tropical legumes increased yield and N content of the subsequent grain corn (Balkcom and Reeves 2005).

Meta-Regression. The mixed models included NFR and WCC termination as explanatory variables, which explained a significant amount of variability in the RR. The main effect of WCC type was significant in the NFR and WCC termination models, which were run independently due to unequal number of observations and to avoid overparameterization if included together in a full model. However, only the interaction NFR \times WCC displayed significant effects on yield response. The regression coefficients for the NFR model were therefore analyzed further (table 6).

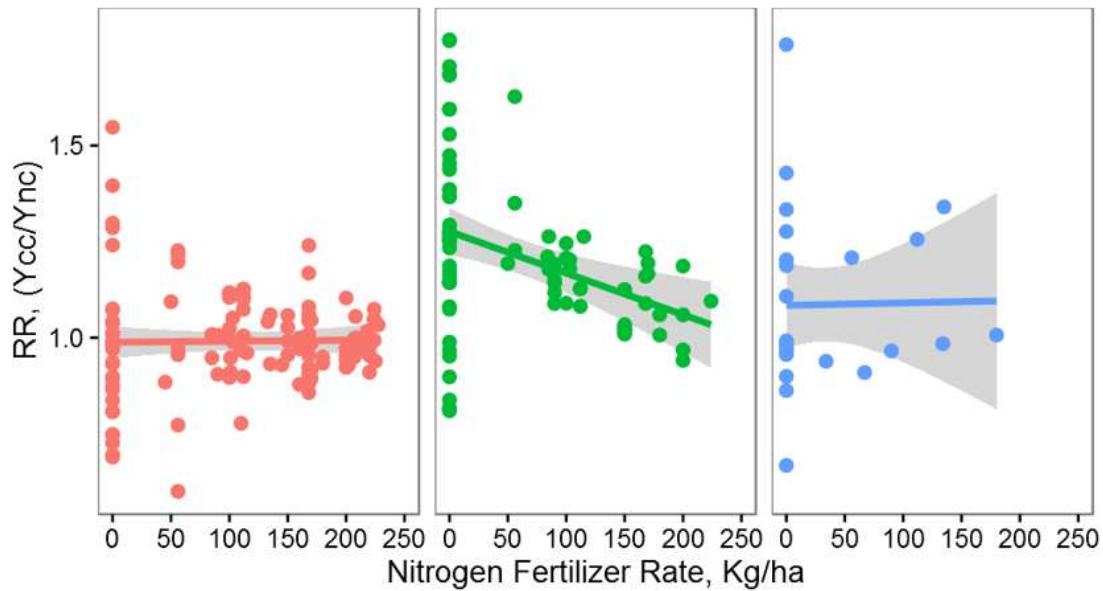


Figure 7. Relationship between the response ratio [yield of corn following winter cover crops/yield of corn following no cover (RR)] and the continuous variable nitrogen fertilizer rate (NFR) for mixture, grass, and legume winter cover crops.

The intercepts for mixture and legume were statistically different from 1 (i.e., no WCCs effect), indicating that yields for unfertilized corn were 18% to 42% greater when the previous WCC was a mixture or a legume. The magnitude and direction of the slope was different for legume and mixture WCCs (figure 7). With increasing N rates, the RR for mixture seems to remain unchanged, whereas the legume RR decreased. The yield gap between corn with WCCs and NC, which is more noticeable at lower N rates and narrows down with high NFR, has been substantiated by previous corn response models (Smith et al. 1987; Miguez and Bollero 2005; Miguez and Bollero 2006).

Table 6. Analysis of variance and estimates for the regression parameters illustrating the relationship between the response ratio (RR) and two explanatory variables [Winter cover crop species (WCCs) and nitrogen fertilizer rate (NFR)]

| ANOVA | | | | | | |
|---------------------|-----------|-----------|----------|----------|----------|----------|
| Source | F | p-value | | | | |
| WCC | 51.63 | <0.001 | | | | |
| NFR | 17.3 | <0.001 | | | | |
| WCC x NFR | 32.13 | <0.001 | | | | |
| Parameter estimates | | | | | | |
| WCCs | Intercept | Lower CL† | Upper CL | Slope | Lower CL | Upper CL |
| Mixture | 1.18 | 1.07 | 1.30 | -0.00076 | -0.00206 | 0.00054 |
| Grass | 0.92 | 0.84 | 1.00 | 0.00030 | -0.00020 | 0.00092 |
| Legume | 1.43 | 1.35 | 1.50 | -0.00340 | -0.00280 | -0.00134 |

[†] CL = 95% confidence limits.

Legume WCC contribution to higher yields at low NFR seems to be related to higher N mineralization, but some studies have found comparable or even greater yields than NC as NFR increases or more than one species is used, suggesting WCC benefits beyond N supply,

such as soil moisture conservation, supply of other nutrients, or reduction of pest pressure (Ebelhar et al. 1984; Blanco-Canqui et al. 2015). For grass WCCs on the contrary, neither the intercept nor the slope were significant in this analysis (figure 7), indicating that corn following grass or NC responded similarly to N (Miguez and Bollero 2005; Pantoja et al. 2015). Grass WCCs do not increase soil N substantially. In fact, N is either retained in the WCC biomass or immobilized by microbes that decompose high C/N ratio residues (Krueger et al. 2010). Even if N is recycled to the soil, the synchrony between high crop demand and N recycling from the residue could simply not occur, for which N application rates for corn under typical management conditions in the Midwest should be the same regardless of the inclusion of grass WCCs (Pantoja 2015).

Table 7. Analysis of variance and estimates for the regression parameters illustrating the relationship between the response ratio (RR) and two explanatory variables [Winter cover crop species (WCCs) and termination (T)]

| ANOVA | | | | | | |
|-------------------------------|-----------|-----------|----------|----------|----------|----------|
| Source | F | p Value | | | | |
| WCC | 36.86 | <0.001 | | | | |
| Termination (T) | 0.06 | 0.801 | | | | |
| WCCs x T | 0.53 | 0.587 | | | | |
| Parameter estimates | | | | | | |
| WCCs | Intercept | Lower CL† | Upper CL | Slope | Lower CL | Upper CL |
| Mixture | 1.19 | 1.06 | 1.33 | -0.00311 | -0.00150 | 0.00866 |
| Grass | 0.96 | 0.89 | 1.05 | -0.00030 | -0.00610 | 0.00535 |
| Legume | 1.27 | 1.19 | 1.36 | 0.00316 | -0.00386 | 0.01007 |
| † CL = 95% confidence limits. | | | | | | |

† CL = 95% confidence limits.

The regression coefficients for the WCCs termination model were not significant (table 7). This result implies that corn yields were not significantly different between WCCs

and NC whether the cover crop was early-or late-terminated. Although the intercept did not differ statistically from 1 in all three WCC types, the RR for legume and mixture was higher than grass for WCCs terminated zero days before corn (i.e., late termination). Similarly, corn yields following legume and mixture were comparable to NC with a slight, yet not significant, increase at early termination (i.e., 14 days or more before corn).

Sensitivity Analysis and Publication Bias. The cumulative meta-analysis by publication year displayed a decreasing but not always significant time trend in yield response to WCCs (figure 8). Thus, only studies from the mid-1980s to early 1990s reported mean RRs that did not encompass 1. Mean RRs for this period were between 1.17 and 1.20, suggesting yields 17% to 20% higher for corn following WCCs. These studies tested WCC performance of different species, but were mostly conducted in the southeast United States (Frye et al. 1985; Varco et al. 1989; Utomo et al. 1990) where positive yields have resulted from soil improvement and N cycling of legume WCCs. On the other hand, before 1985 or after 1991, CMA revealed a decreasing yet not statistically significant trend of yield response to WCCs. Interestingly, for the time period considered for this meta-analysis update (2005 to 2015), RRs were not different from 1. Comparable yields for corn with and without WCCs in this period are the result of research with predominance of grass WCCs in the North Central United States, which were shown to pose neutral effects on subsequent corn.

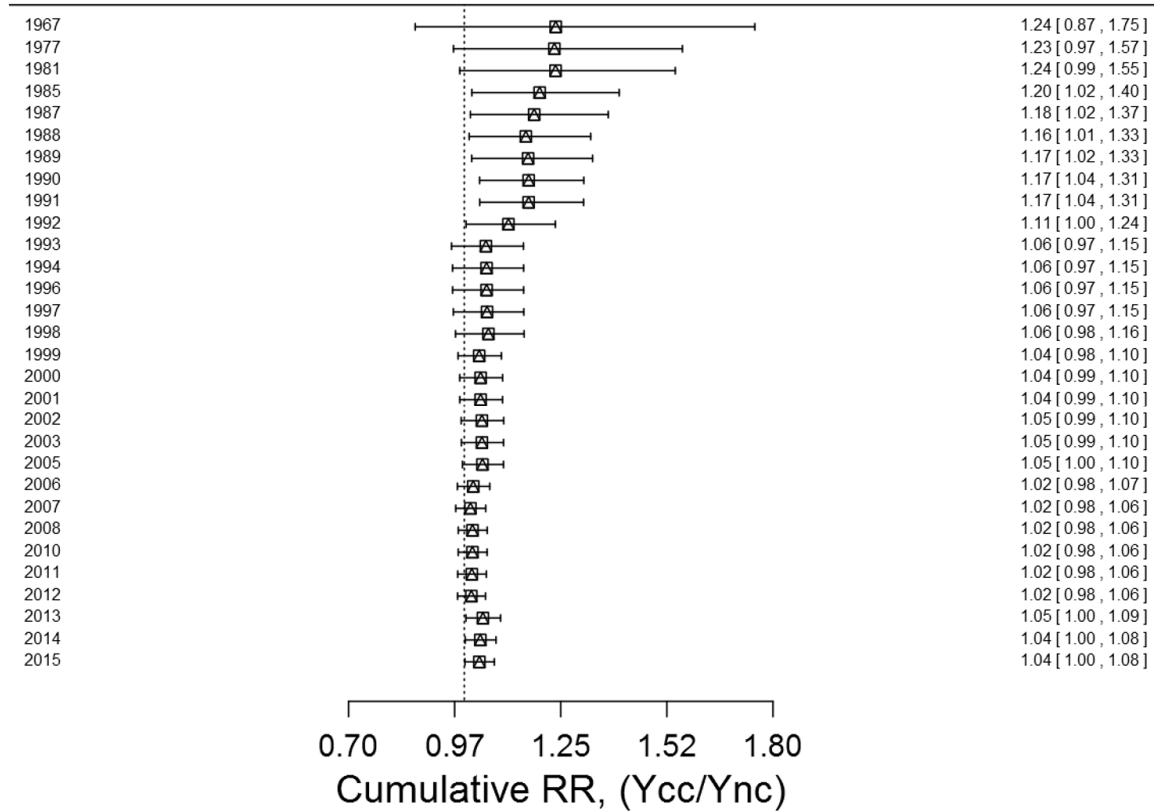


Figure 8. Cumulative response ratio [yield of corn following winter cover crops/yield of corn following no cover (RR)] and 95% confidence interval (horizontal bars). A ratio represents the cumulative weighted mean computed for all the studies published in the same year.

Noticeably, CMA demonstrates that the uncertainty around the mean response (95% CI) has been reduced since the first publications in the late 1960 to early 1970s, which changed considerably in early studies and stabilized as the whole set of studies was completed. CMA in other biological sciences have shown similar reductions in uncertainty around cumulative mean effect sizes when the time span of analysis was large and study distribution was uneven (Leimu and Koricheva 2004; Simmonds et al. 1999). From the sensitivity analysis, we found that as yield response to WCCs stabilizes and uncertainty around the RR decreases, a more adequate description of overall effect is expected. However, the exploration of corn yield progression affected by WCCs was not exhaustive, and future

research should consider analyzing the sensitivity of results to factors other than publication year, such as journal impact factor or study time length.

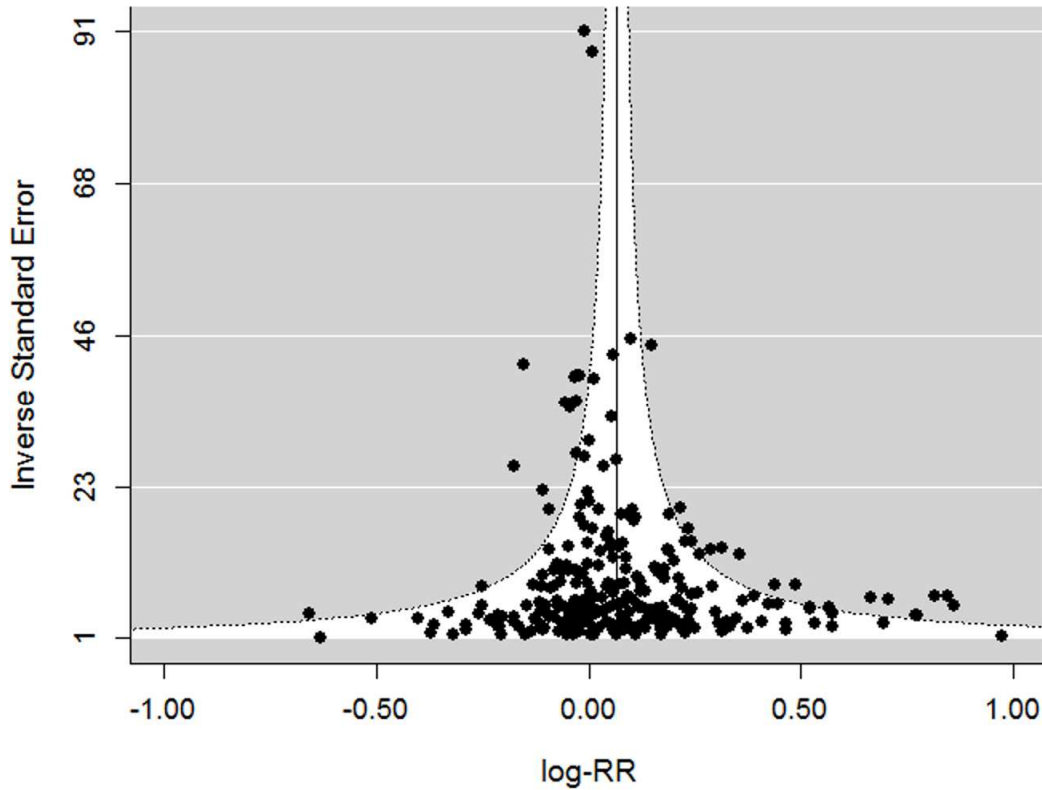


Figure 9. Inverse standard error associated with each observation included in the meta-analysis against effect size [log (yield of corn following winter cover crop/yield of corn following no cover)].

Publication bias was not detected through funnel plots of RR against a measurement of study variability (i.e., inverse of standard error). Individual RRs were symmetrically distributed around the mean effect size (figure 9). As in the previous meta-analysis, no direct relationship emerged between RR and precision (i.e., lower study variance) (Anzures-Cabrera and Higgins 2010), for which reports of exclusively significant WCC effects in our data set were unlikely.

Summary and Conclusions

We updated the overall corn yield response to WCCs based on peer-reviewed publications from the last ten years (2005 to 2015). The authors confirmed and expanded the conclusions of the previous meta-analysis regarding WCC contribution to corn yields. Evidence from this update suggests an overall neutral to positive influence of WCCs on corn production in the United States and Canada. Much of the variability in WCC effects reported among publications arise from differences in management across regions. On average, grass WCCs neither increased nor decreased corn yields, although corn grown for grain yielded relatively higher than silage corn. In turn, mixture WCCs show an overall positive effect on corn yields, which is significantly higher at late termination of the cover crop. Legume WCCs contribute to higher corn yields when N fertilizer rates are low, or the tillage systems shifts from CT to NT. When analyzed in retrospective, however, WCCs contributed to higher corn yields mainly during the mid-1980s to early 1990s. Early research during this period emphasized testing of WCC species with potential to establish early and provide benefits under warmer conditions. WCC research of the last decades summarized for this review, however, has been directed towards practices that address challenging conditions for establishment in temperate areas, where soil benefits can be maximized but corn yields are not directly improved. The evidence in this review shows the potential of WCCs to maintain or increase corn yields. However, incentives for WCC adoption should also consider factors beyond expectations for yield increases, such as improvements in nutrient cycling, water conservation, and erosion control. Because of future changing conditions to which farmers must adapt, results from this review should guide future evaluation of topics of limited exploration to date, such as field experiments involving more diverse WCC mixtures, or quantitative assessments of long-term cover crop impacts on soil and water conservation.

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Appendix

Table A1. Appendix. Reference, location and species used from 28 studies in the updated meta-analysis (2005-2015).

| Reference | Location | WCC species ² |
|---------------------------------------|--------------------------------------|--------------------------|
| Andraski and Bundy 2005 | Hancock, WI | G |
| Balkcom and Reeves 2005 | Shorter, AL | L |
| Bich et al. 2014 | Andover. Trail City. Aurora, SD. | M |
| Bundy and Andraski 2005 | Hancock, WI | G |
| Crandall, Ruffo, and Bollero 2005 | Urbana, IL | G |
| Dietzel et al. 2016 | Boone, IA | G |
| Duiker and Curran 2005 | Rock Springs, PA | G |
| Fronning, Thelen, and Min 2008 | East Lansing, MI | G |
| Hashemi et al. 2013 | South Deerfield, MA | G |
| Kaspar and Bakker 2015 | Boone, IA | G |
| Kaspar et al. 2012 | Boone, IA | G |
| Kaspar et al. 2007 | Boone, IA | G |
| Krueger et al. 2011 | Morris, MN | G |
| Lawley, Weil, and Teasdale 2011 | Beltsville, MD | G |
| Miguez and Bollero 2006 | Urbana, IL | G, L, M |
| Moore et al. 2014 | Boone, IA | G |
| Mourtzinis et al. 2015 | AL | G |
| Olson, Ebelhar, and Lang 2010 | Dixon Springs, IL | G |
| Pantoja et al. 2015 | Boone. Crawford., Lewis, Nashua, IA | G |
| Parkin and Kaspar 2006 | Boone, IA | G |
| Parr et al. 2011 | Plymouth. Salisbury, NC | L |
| Reese et al. 2014 | Andover. Trail City, SD | M |
| Singer and Kohler 2005 | Boone, IA | G |
| Singer, Cambardella, and Moorman 2008 | Boone, IA | G |
| Smith, Gross, and Robertson 2008 | MI | L, M |
| Thilakarathna et al. 2015 | Elora, Ontario (CAN) | L, G |
| Welch et al. 2016 | Cerro Gordo, IL; Malta, IL; Pana, IL | M |
| Wortman et al. 2012 | Mead, NE | M |

¹For a full description of the studies in the first meta-analysis (1965-2004), see Appendix A in Miguez and Bollero (2005)

² Winter cover crop species: L=Legume, G= Grass, M= Mixture.

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CHAPTER 3. MAIZE SYSTEM IMPACTS OF COVER CROP MANAGEMENT DECISIONS IN IOWA: A SIMULATION ANALYSIS OF RYE BIOMASS RESPONSE TO PLANTING POPULATIONS

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Abstract

Cover crops in the US are incorporated into annual rotations following the harvest of maize or soybeans. In the US upper Midwest, grain harvest is nevertheless followed by cold winters that limit cover crop establishment, survival, and growth. Winter rye (*Secale cereale* sp.) is the most commonly used cover crop among producers because it overwinters and produces considerable biomass in the spring. Field experiments and quantitative reviews of the literature have shown soil and water quality benefits, without yield penalties, when rye is part of an annual maize rotation. The extent to which maize yields and soil-water benefits change under different rye planting densities, however, has not been fully explored. Shoot biomass of a fall-seeded rye cover crop is expected to respond to increasing plant populations (PP), influencing overall maize system productivity, and providing additional income for growers to justify the high establishment costs of the cover crop. We pursued the following objectives: 1) Quantify the relationship between rye biomass and rye PP, 2) Test if this relationship is further controlled by maize Nitrogen (N) rates or vary across locations and soil types, 3) Investigate if changes in maize system outcomes, i.e. grain yield, nitrate leaching,

soil erosion, and runoff are significantly related to rye biomass, and 4) Estimate changes in farm returns for maize operations that utilize rye biomass under alternative scenarios (i.e. grazing). Field data for long-term impact studies is costly and hard to generalize, so we used 25-year weather records (1990-2015) to run the field scale model APSIM and simulate a maize/rye rotation for three locations in Iowa. Overall, we found a positive relationship between rye biomass and PP, with spring biomass increasing by 30% when populations double. No evidence for a biomass plateau was found, although spring biomass differed by soil type and location. Furthermore, relative changes in soil erosion, N-leaching, and water runoff rates were negatively correlated with rye biomass (-1% to -14% change relative to no cover crop, $p < 0.05$). Rye cover crop was shown to reduce annual farm income across Iowa (-8900 to -4000 \$. year⁻¹), but losses were reduced for early grazed rye (-1903 to +1479 \$. year⁻¹) and late grazed rye (-1206 to +12778 \$. year⁻¹). Results from this simulation study indicates that cover crops would effectively benefit overall maize system performance although the economic incentives for increasing rye populations are not generalizable to every location in Iowa.

Keywords. Cover crops, maize, rye, erosion, grazing, APSIM

Introduction

Cover crops are species included between phases of commercial production, usually without returns other than providing environmental benefits. When included as part of a maize rotation, cover crops sequester off-season nutrients and help mitigate risks of a bare fallow field, such as erosion, nitrate leaching, and water runoff, if used in conjunction to reduced tillage or other conservation practices. Research regarding cover crop benefits has

been extensive, with some studies showing 30 to 70% reductions in nitrate concentration from tile-drained water in maize/cover fields (Kaspar, Jaynes, Parkin, & Moorman, 2007), and others reporting 10 to 60% reductions in water runoff and interrill erosion rates of rye treated plots compared to fallow (Kaspar, Radke, & Laflen 2001). Soil and water benefits from a cover crop, however, depend on successful establishment to materialize. Growers in Iowa, especially those in northerly areas in the state, deal with short periods between maize harvest and the frost period, for which small grains can be the only viable option to establish a fall-seeded cover crop that withstand the long winters and resumes growth in spring (Kladivko et al. 2014).

Cereal rye outperforms other small grains because it can tolerate extremely low temperatures (Griffith & McIntyre, 1993) and is able to produce biomass in spring after the dormancy period. While the benefits of incorporating a rye cover crop to an annual maize rotation are evident, gaps persist in regard to changes expected for soil and water conservation if management of the cover crop changes. Further, farmers are uncertain whether adopting conservation practices will ensure that they reap agronomic benefits while being still economically sound.

Most maize growers in the US are still reticent to plant cover crops due to an apparent lack of incentives (Franzluebbers, 2007). Farmers acknowledge the long-term contribution of cover crops to improving soil and water quality (Arbuckle & Roesch-McNally 2015), but such benefits are hard to monetize. In planning cover crop planting strategies, however, growers might utilize the biomass gains that result from increasing plant populations of the cover crop. Farms that integrate crop and livestock operations can take advantage of the additional forage supplied by a fall-seeded cover crop (Bergtold, Ramsey, Maddy, &

Williams, 2017), and grazing rye biomass would reduce the dependence on hay, silage, or other forage sources during the winter and spring months. Harvesting rye biomass may help, in addition, to offset the high costs associated with establishing a cover crop, especially if a grower lacks support from subsidies, cost-share, or other assistance programs.

While small grains can compensate low planting densities through intraspecific mechanisms of competition, such as tillering and higher morphological plasticity, i.e. modify growth habits to occupy more space (Evers, Jan Vos, Andrieu, & Struik, 2006), increasing plant populations (PP) has been traditionally proposed to increase biomass and grain yields (Chen, Neill, Wichman, & Westcott, 2008). However, much less has been investigated from the perspective of planting cereal cover crops at different population ranges and still obtain soil and water benefits while avoiding reductions in subsequent maize yields. The few studies addressing this question, have documented a positive response of cover crop biomass at higher rye populations (Boyd et al. 2009; Brennan & Boyd 2012) with some observing that biomass and nitrogen uptake of the cover crop often correlate positively (Hashemi et al. 2013). Additionally, it has been suggested that increased biomass of a winter cover crop may lead to possible reductions in nitrate leaching, run-off, or erosion rates (Basche et al., 2016) albeit quantification of such relationships at varying rye plant populations, different climates, or soil types has not been yet explored.

Because biomass of a fall-seeded cover crop may be management dependent and would impact the maize system overall, we propose a simulation study to: 1) Evaluate quantitatively the relationship between biomass and rye cover crop PP, 2) Test whether the biomass response to PP is moderated by maize N-rates, or vary across different location and soil types, and 3) Investigate if changes in maize system outcomes, i.e. grain yield, nitrate

leaching, soil erosion, and soil-water runoff, are significantly related to rye cover crop biomass. As cover crop management causes farm impacts that extend beyond the purely agronomic, we also include a short-term economic analysis of rye biomass utilization. Specifically, we analyze projected changes in farm returns for a maize-livestock operation that utilizes rye biomass as an alternative grazing source.

Materials and Methods

Process based models are valuable tools for assessing crop impacts outside the domain of a single field. Evaluating the impact of cover crops on maize cropping systems is challenging as multiple processes involving soil, plant and the atmosphere come into play, making it difficult for traditional field approaches to capture responses at every level of detail. APSIM (Agricultural Production System Simulator) is a physically-driven model that simulates crop growth using resource capture and transformation approaches and describes multiple dynamics in a crop system. APSIM integrates independent plant and soil modules into a central engine where crop and soil processes are represented by system variables, which are updated at a daily time step (Keating et al. 2003). In addition, it has been successfully adapted to model maize rotations and analyze impacts known to cover crops, such as N scavenging and soil carbon formation (Basche et al., 2016), soil water dynamics (Dietzel et al. 2016), or abiotic processes affected by extended cover crop use (Martinez-Feria, Dietzel, Liebman, Helmers, & Archontoulis, 2016).

Three steps were followed to accomplish the goals of the study: 1) Calibration of the plant and soil components for the maize/rye rotations simulated in APSIM; 2) Design of the long-term simulation, with rye PP combined with different soil types and maize N rates in a factorial arrangement; and 3) Statistical evaluation of model outputs for a more

comprehensive analysis of the relationship between maize system performance and rye biomass.

Model calibration and validation. Maize and rye biomass in APSIM results from radiation interception and is further limited by water and N supply. In addition, phenology is represented by 10 phases limited by thermal time accumulation, with additional effects of photoperiod (i.e. daylength) and vernalization (i.e. cold requirements for flower initiation). Photoperiodic and vernalization effects are cultivar sensitive and expected to determine changes in rye phenology, but a single winter cultivar was assumed for the simulations at the three Iowa locations (North East, Central West, South West). Because a cover crop module is currently unavailable in APSIM, the american wheat cultivar “yecora” was calibrated against field records available for: 1) Fall and spring shoot biomass (kg. ha^{-1}), and 2) Fall and spring N-content in rye biomass (kg. ha^{-1}). We replicated the calibration published by Basche et al., (2016) based on minimizing error between model predictions and observed maize yields and rye biomass recorded in a long-term cover crop trial in Iowa, spanning 10 years of data available for model validation (2002-2012). In addition, phenological representation of the rye cover crop was improved with a new dataset available on vegetative stages recorded at the same site during the 2015-2017 cover crop seasons. The Kelly Tile Experiment (Kaspar et al., 2007; Basche et al., 2016) is located in Boone, IA (42.05 N, 93.71 W) and has been in place to evaluate the long-term contribution of fall-seeded cover crops to maize and soybean systems since 1999. Maize parameters were adjusted to represent phenology, biomass, and yields of a standard 110 RM (relative maturity) hybrid adapted to the US Midwest. Main field operations, hydraulic soil properties, and rye and maize parameters used in the APSIM simulations are shown in table 1.

Selected properties were adjusted to simulate water retention and drainage conditions of three soils: Fayette, Nicollet, and Sharpsburg. Each soil represents a major soil series of the Iowa's Northeast, Central West, and South West regions respectively (Fenton, Duncan, Schrader, & Dumenil, 1971). Textural conditions of the three soils differ, and drainage decrease from high to low in the following order: Fayette (silt-loam) > Sharpsburg (silty-clay-loam) > Nicollet (loam). First, we set the air dry, and upper and lower retention limits required by APSIM to control water content available for maize and rye uptake. Plant available water for maize and rye was assumed the same, and was defined at 310 mm for Nicollet (depth=1850 mm), 200 mm for Sharpsburg (depth=1500 mm), and 230 mm for Fayette (depth=1600 mm). As recommended by other modeling studies of hydrological processes in field crops (Ma et al., 2007; Malone et al., 2007) hydraulic conductivity at the bottom layer was set at a very low values relative to the surface to avoid model failure and simulate water table effects on downward flow more satisfactorily.

Drainage management in Iowa is site-specific and was modeled accordingly. Sloan, Mantilla, Fonley, & Basu (2017) showed major presence of tiles in Iowa's central districts whereas coarser textured soils in northeastern and most parts of the southern portion of the state usually would not require controlled drainage conditions. Thus, for the moderately and well drained soils (Sharpsburg/South West and Fayette/North East) water flow was better modeled using the default "typing-bucket" approach (soil-wat) in APSIM. In contrast, the alternative module SWIM, based on iterative solution of Richards equation for unsaturated flow, modeled downward flow more satisfactorily than the default water-balance approach for the poorly drained Nicollet soil in Central West Iowa. The SWIM module was also included to represent a tile drainage system, commonly used in this region to improve

drainage and maintain optimal moisture levels for maize growth. When base calibrations failed to provide good starting conditions for maize/rye germination, soil properties were further adapted to “expert” opinion or the soil web survey (Archontoulis, Miguez, & Moore, 2014; USDA-Soil Survey, 2017).

Long term simulation experiment. A factorial experiment was designed to simulate biomass response to different rye PP (n=4), maize N-rates (n=2), and soil-locations (n=3). Soil types (Fayette, Sharpsburg, Nicollet) were the upper nodes in the simulation tree. Location was nested into soil type (North East/Fayette, South West/Sharpsburg, Central West/Nicollet) and was specified by its own weather file, including 25-year records (1990-2015) on solar radiation, maximum and minimum temperatures, and precipitation. Weather records were obtained from daymet (Daymet V3., 2016) for three Iowa counties representative of each location (Clayton/North East, Adams/Sharpsburg, Boone/Central West). The next branches in the design were: rye plant population at sowing (n=4), coded as a factor and ranging from 150 to 450 plants.m⁻² at 100-plant intervals, and maize N fertilizer (n=2), evaluated at 150 and 300 kg. ha⁻¹. Maize N rates reflects only an initial surface application of urea during maize sowing. Six hundred predictions were collected on rye biomass, water runoff, N-leaching, and soil erosion by running 24 factorial combinations (Soil/Location x rye-PP x maize-N) during 25 years of weather data. Concurrently, a set of maize simulations without cover crop were run for each soil/region and controlling only for the two N fertilizer rates (Soil/Location x maize-N x year, n=150).

Maize simulations with and without rye were initially run for a 9-year warm-up period to stabilize soil processes affected by crop residue decomposition (i.e. 1980-1989). Initial surface residue from the rye cover crop was set at 1000 kg. ha⁻¹ on an 80:1

carbon:nitrogen ratio. Long-term simulations were run continuously and without resetting soil water conditions each year. Other maize and cover crop operations were hold constant. May 1 and September 30, for example, referred to maize sowing and harvest in a year whereas October 1 and April 25 of consecutive years separated drill-seeding and termination of the cover crop.

Statistical summaries. Statistical evaluations were conducted to summarize and interpret rye and maize model outputs. Different models were tested to detect the contribution of each factor on rye biomass variability, of which, PP and soil type were the most significant. Thus, a polynomial mixed model (equation 1) was fitted to APSIM predicted biomass, including a quadratic effect for PP, linear effects for soil type and its interaction with PP, and a random-intercept term to account for year variability. The mixed model captures biomass differences arising from weather variation and APSIM predictive capabilities while summarizing the data with a few parameters.

$$B_{ijk} = \beta_o + \beta_j soil_{(Location)} + \beta_i PP + \beta_{ij} PP \times soil - \beta_i PP^2 + b_k year + e_{ijk} \quad (1)$$

The polynomial model was used in turn to compute average (BA), marginal (BM), and relative (BR) changes in biomass due to rye PP for each soil/location (equations 2, 3, and 4).

$$BA_{ij} = \frac{B_{ij}}{PP_i} \quad (2)$$

$$BM_{ij} = \frac{dB(PP_{ij})}{dPP_i} \quad (3)$$

$$BR_{ij} = \frac{\% \Delta B_{ij}}{\% \Delta PP_i} \approx \left(\frac{dB_{ij}}{dPP_i} \right) \left(\frac{PP_i}{B_{ij}} \right) \quad (4)$$

B represents biomass for the j-th soil/location predicted at the i-th PP. Average biomass is the ratio between biomass and the PP at which it was predicted. Marginal biomass referred to the biomass increase rate per-unit increase in PP and was evaluated as the first derivative of the quadratic model estimated for rye biomass with equation 1. Relative biomass is the ratio between rates of change in biomass and PP respectively, and can be interpreted as an elasticity-ratio, or the product between marginal biomass and the inverse of average biomass. Relative biomass can be interpreted as the percentage increase expected in biomass for a one percent increase in PP, or how sensitive the prediction of biomass becomes at small increments in PP.

An additional evaluation was performed on maize system outputs to analyze how these are related to cover crop biomass. Maize grain yield (kg ha^{-1}), subsurface drained nitrate ($\text{kg N ha}^{-1} \text{ year}^{-1}$), soil loss (Mg year^{-1}), and runoff (mm) predictions were sorted and compared between simulations with and without the cover crop. After checking for differences due to rye PP, maize N-rate, site or region, the aforementioned indicators were averaged, and relative change rates were computed. A relative change rate was estimated as the difference in maize indicator (Y) with and without cover crop divided to maize indicator without cover (equation 5).

$$\text{Relative change rate} = \frac{Y_{\text{cover}} - Y_{\text{no.cover}}}{Y_{\text{no.cover}}} \quad (5)$$

Pearson correlation tests were run between maize relative changes and cover crop biomass at each level of the factors deemed most significant. Maize and rye simulations were run using a hierarchical factorial structure in APSIM version 7.8, and results were exported and evaluated using libraries (e.g. lme4, apsimr, apsim, xml) available in the R statistical software version 3.3.2 (R Development Core Team, 2017).

Economic Analysis. Results from the agronomic simulations were used to calculate simplified budgets for a maize-cattle operation that grazes rye biomass under two grazing scenarios. Rye populations (PP) at 150 and 350 plants.m⁻² were chosen to represent hypothetical “low” and “high” planting decisions. Rye biomass and maize yields simulated at these two rates were then used as the main inputs to run the Iowa budget decision tool for cover crops economics (Edwards, Plastina & Filbert, 2018). This decision tool allows a user to calculate net changes in farm income resulting from the direct economic impacts of the cover crop minus establishment and operation costs of a maize-livestock operation. The major shift in income was given by the estimated value of feed replaced by rye biomass in a grazing period. Also, positive income changes were determined by any percent increase in maize yields following the cover crop. We defined two scenarios: a) an early grazing period (Oct/25-Mar/25), and b) a late grazing period (Nov/15-Apr/15). Late and early grazing periods differed in terms of the expected biomass production of the cover crop.

The two grazing scenarios were run on the three Iowa districts used for agronomic simulations of rye response to PP (i.e. North East, South West, Central West); each characterized by a different length of the growing season limiting rye growth. Common to every region, we assumed a farm with 200 acres planted to cover crops following maize

harvest. Cattle stock for a farm of this size consisted of 100 animal units including dry, lactating, and heifer calves. Further, we assume that costs of rye establishment and termination were constant across regions and seeding rates. Rye populations and seeding cost assumptions are described in tables A1, A2, and A3 (appendix). Further cost and revenue calculations in the partial budget tool are out of the scope of this study but interested readers can refer to Edwards, Plastina, & Filbert (2018).

Results and Discussion

Model validation. Cover crop biomass was adequately simulated for the validation period at the Iowa Kelly site (2002-2012, figure 1). Mean predicted fall and spring biomass were $188 (\pm 46.3)$ and $1905 (\pm 292)$ kg. ha⁻¹ whereas observed biomass were between $140 (\pm 28.5)$ and $1977 (\pm 226)$ kg. ha⁻¹ respectively. Model prediction error (Root mean squared error, RMSE) was 80 and 466 kg. ha⁻¹. Overall, biomass was predicted between 23 and 56 % around the mean observed biomass for the 2002-2012 period (RRMSE_{fall} = 0.23, RRMSE_{spring} = 0.56).

Predicted fall and spring N content in rye biomass for the 2002-2012 period were $10.2 (\pm 2.54)$ and $40.8 (\pm 7.19)$ kg. ha⁻¹. Observed N contents were $5.39 (\pm 1.29)$ and $46.8 (\pm 3.32)$ kg. ha⁻¹ for the fall and spring seasons respectively. Nitrogen content in biomass was modeled more accurately during spring. Model prediction errors for the fall were 6.01 kg. ha⁻¹ (RMSE) and 1.12 (RRMSE) whereas those for the spring were 16.03 and 0.35 kg. ha⁻¹.

Differences in agreement between predicted and observed rye biomass resulted mainly from the different planting conditions considered in our validation dataset. Biomass accumulation during the fall period was generally low regardless of the planting strategy, but prediction errors for spring biomass were more evident in years where rye was broadcast-

seeded. Rye N-content was predicted more accurately during spring, likely as the result of active periods of cover crop growth and soil water transport (e.g. freeze/thaw soil cycles) following the winter months (November-February). In general, most years fell within reasonable limits relative to the predicted: observed agreement lines for biomass and N-content displayed in figure 1. Moreover, model predictions were validated within rye populations between 200 and 400 plant.m⁻² estimated at the field site, and therefore, APSIM was shown to be robust enough to assess long-term biomass responses to a range of similar planting densities.

Long term biomass response to rye populations. Model simulations showed a positive and increasing non-linear relationship between rye biomass and plant populations (figure 2). Such a response reflects the well-known effect of increasing plant seeding rates to maximize vegetative growth and yields of winter and spring cereals. However, no visual indication of plateaus, or inflexion points were evidenced in the plots between total spring biomass (i.e. biomass estimated at cover crop termination) against PP. Further, biomass response to PP varied between soil types but not across maize- N rates. Predicted biomass for a rye cover crop increased for increased PP, especially when soil drainage improved and location allowed for favorable conditions for growth (Table 2). Mean biomass of a rye cover crop was higher at every PP on the mid-drained soil (Sharpsburg) in South West Iowa (figure 2), ranging from 2500 to 4000 kg ha⁻¹. These model estimations agree well with farm and modeling studies across the US Midwest, where rye biomass has been reported to reach values around 2000 kg ha⁻¹ or above when seeded as a single species between maize and soybean cycles (Boyd et al., 2009; Brennan & Boyd, 2012; Dietzel et al., 2016).

Rye biomass increased at every PP but biomass productivity ratios were always diminishing (figure 3 panels A, B). The Sharpsburg soil in South West Iowa, displaying moderate drainage conditions, showed again the highest rates for average and marginal biomass. For a three-fold increase in PP, for instance, average and marginal biomass rates of change (i.e. biomass productivity per plant) declined from 1.6 to 0.9 g. plant⁻¹ and 0.8 to 0.3 g. plant⁻¹ respectively, although the reduction was more drastic in the poor and well drained soils (Nicollet and Fayette). It is expected that additional seeding rates beyond the chosen PP would always produce fewer gains in biomass, yet moderate soil drainage conditions and favorable weather for extended growth in strategic locations across the state would also offset this reduction in productivity. The analysis in relative terms revealed also that biomass gain differences were notably among soils. Percent biomass gains increased at low PP, peaked at mid PP ranges, and declined thereafter (figure 2, panel D). Interestingly, the highest relative gains in biomass at a low PP (200 plant m⁻²) were noted in the less favorable Fayette soil in North East Iowa (~ 0.60 %). For moderate and well drained soils on favorable locations with longer growing seasons (Sharpsburg/South West, Nicollet/Central West), peaks in relative biomass were found at mid PP (i.e. ~ 0.50% at 250 plant m⁻²). This last finding suggests a good expectation for biomass accumulation and subsequent benefits for moderate increases in PP when drainage of an Iowa soil is adequate, and cover crops can benefit from longer periods of growth. Seeding rates beyond 450 plants m⁻², regardless of soil type or location would bring marginal gains that would not compensate for the additional costs associated with them.

Different biomass responses between soil types have been documented for cereal rye when adapted as a cover or forage crop, and have been attributed to optimal shoot/root

balances that occur when drainage and fertility of the soil improves (Blanco-Canqui et al., 2015; Alvarez, Steinbach, & De Paepe, 2017). Sharpsburg in South West Iowa is a silty clay loam with moderate drainage, while excess water can be effectively controlled with tile drainage systems in the poorly drained Nicollet soil in Central West. Fayette, on the contrary, represents a predominantly coarser textured soil with poor water retention capabilities, typical of major areas in North East Iowa. Besides the advantages for warmer temperatures and extended growing seasons to grow cover crops in Central and South West Iowa, larger biomass estimates may have been also the result of improved soil water retention. Adequate drainage reduces the risk of nutrient leaching and soil moisture remained at levels where root development is favored, likely supporting the increasing pressures for water and nutrients by higher rye populations.

Rye biomass effects on nitrate leaching. Nitrate in subsurface drainage was consistently lower for the simulations involving a rye cover crop (table 3). For the time period considered (1990-2015), mean nitrate leaching for maize without a cover crop ranged between 20.11 and 28.59 kg N-NO₃ year⁻¹ whereas that including rye, and regardless of the seeding rate applied, was reduced to 5.98 and 8.93 kg N-NO₃ year⁻¹. Our results are in line with research reports of nitrate leaching as high as 30 kg N-NO₃ for the US corn belt, and that could reach values beyond 50 kg N-NO₃ in wet years (Kladivko et al. 2014; Kaspar, Jaynes, Parkin, Moorman, & Singer, 2012). Our findings also demonstrate the effects of weather variation, alongside different cropping strategies, which may accentuate the complexity of N dynamics in the soil (Asseng et al., 1998; Plaza-Bonilla, Nolot, Raffaillac, & Justes, 2015). Also, nitrate leaching was negatively correlated with biomass accumulation at any PP of the rye cover crop ($r = -0.37$, $p < 0.001$, $n=75$). This negative linear effect

suggests a higher nitrate uptake by the cover crop as biomass increases, which would have otherwise ended up leaching (figure 4). To corroborate this relationship, we ran independent model checks and found a positive relationship between N-content in rye biomass and total biomass accumulation (data not shown). In addition, cover crop N uptake would also have contributed to reduce soil nitrate levels, as field research has demonstrated higher leaf-N concentration and reduced soil nitrate levels detected during periods of active cover crop growth (Yu et al., 2016).

Rye biomass effects on soil erosion. Soil loss rates were likewise diminished in the maize-rye simulations (table 3). Across soil-locations, mean soil loss-per-year with cover crop was modeled in the 0.88-5.27 Mg. ha⁻¹ range while no cover averaged between 2.51 and 15.86 Mg. ha⁻¹. No significant effect was detected for PP in moderating this effect. The APSIM long-term averages presented here range between low to high, and soil loss rates can be subjected to significant year-to-year variation, soil composition, or crop practices in place (e.g. reduced tillage, residue management, etc.). Although soil loss predictions in our simulations are representative of national averages of nearly 17 Mg. ha⁻¹ of soil that get lost from US cropland every year (Pimentel, Hepperly, Hanson, Douds, & Seidel, 2005), the parameters chosen to control erosion in APSIM equations may not be fully representative of all terrain conditions across the three locations in our analysis (e.g. % terrain slope, erodibility factor, farm practice). Further, it is worth noting the complexity involved in predicting soil loss, for which field-scale models like APSIM may still fail to capture the whole suite of cover crop benefits in reducing erosion.

Soil loss (%) was found to decrease, i.e. larger negative figures, as biomass of the cover crop increased ($r = -0.38$, $p < 0.001$, $n = 75$). (figure 4). Cover crop benefits in offsetting

erosion usually are two-fold: 1) slow residue turnover and decomposition, which provides a barrier against running water and aggregates breakdown, and 2) reduced soil detachment and transport due to densely extended roots (Kaspar, Radke, & Laflen 2001). Because of the scope of this work, however, modeling root growth and belowground performance of the cover crop was not carried out and future research in this area is suggested.

Rye biomass effects on runoff. Runoff simulations were lower for the maize-cover crop treatment (table 3). Across soil types and locations, annual mean cumulative run-off with a cover crop was estimated between 35 and 193 mm while no cover averaged between 29 and 163 mm. Runoff reduction varied among soils. Despite being inherently a poorly drained soil, Nicollet experienced the highest runoff reductions in maize-cover simulations presumably due to the model capturing the enhanced drainage effects by the tile system.

Runoff in our simulations occurred mainly during periods where rainfall exceeded soil infiltration. Previous works have pinpointed runoff reduction benefits due to canopy development of the cover crop, which provides a mechanical barrier to reduce kinetic energy of running water, or through transpiration of the cover crop. In our study, most of the results could be attributed to such aboveground mechanisms. However, it has been shown that root architecture of the cover crop may bring structural enhancement and subsequent reductions in runoff and erosion via two pathways, 1) through long-term aggregate stabilization, driven by increased root density and root volume, and 2) by increasing macropore numbers for rapid infiltration (Yu et al. 2016; Kaspar, et al., 2001).

A negative albeit non-significant relationship held between runoff and increasing biomass (figure 4) ($r = -0.016$, $p = 0.89$, $n = 75$). These results suggest that both above and belowground contribution of the cover crop were captured by APSIM: higher transpiration

rates of a larger canopy, augmented by increased PP; and, improved hydraulic properties of the soil. It should be noted that soil practices, such as tillage or residue incorporation, are major modifiers of soil water dynamics but were not explored in the study.

Rye biomass and maize grain yields. Out of the five performance indicators, maize yield predictions exhibited the least variation among treatments. Across soils and locations, maize yield with cover crop averaged 10,458 kg ha⁻¹ [range= 9,425; 10,958] for the 25-year period, comparing relatively higher to no-cover, which averaged 10,433 kg ha⁻¹ [range= 9101; 10,922]. Because yield is the result of diverse processes at the soil, plant, and atmosphere levels, biophysically oriented models capture and model efficiently the gains and losses derived from such interactions. APSIM, in particular, has been validated against field data from multiple years and management scenarios in the US northern corn belt, providing reasonably accurate yield predictions that agree well with the simulations presented here (Archontoulis et al., 2014; Basche et al., 2016). For reference, maize yields in this area have grown steadily through decades of improvement in farm technology and genetic materials, so that average yields may well go beyond the 13,000 kg. ha⁻¹ (~ 200 bushel/acre) mark.

No significant effects were detected in maize yields with cover crop due to rye PP or maize-N rates. We confirmed the expectation of neutral yield effects of the cover crop by comparing yield rate and rye biomass ($r = 0.0087$, $p = 0.46$, $n = 75$) (figure 4). Data reviews have estimated a neutral cover crop contribution to maize yields (Marcillo & Miguez, 2017; Miguez & Bollero, 2005). However, maize with cover crops could yield slightly above or below no cover depending on management conditions. For example, legume cover crops were shown to increase maize yields by 21% when tillage was reduced whereas grass species

(e.g. winter rye) in association with legumes may suppress weeds for overall yield gains of around 13% relative to no-cover crop (Marcillo & Miguez, 2017).

The cases where yield reductions do occur still remain open for further research, and have been attributed to nutrient immobilization, water competition, disease or pathogens. (Alvarez et al., 2017; Kaspar & Bakker, 2015; Singer & Kohler, 2005). Here, model predictions for a year where a yield penalty occurred may have resulted from N immobilization by the rye residue; exacerbated because of the somewhat strong assumption of a fixed termination date every year. On model checks, strong rates of N immobilization occurred frequently in late spring, beyond late April to Mid-July, and were worsened in dry years. Also, rye is not a strong source of N release due to its slow decomposing residue. Soil water competition may be unlikely because soil water lost to rye transpiration is usually replenished by the rainfall typical in the US Midwest (Basche et al., 2016b).

Economics analysis of rye biomass in maize-cattle operations. Net income would be severely reduced if rye biomass were left ungrazed (table 4, table 5). Yearly losses under this scenario amounted to \$8,900 in the most affected district (North East). Overall, grazing rye biomass was found to buffer farm losses incurred in establishing the cover crop although the magnitude of loss, or gain in some cases, differed between grazing periods. Different margins between grazing scenarios were expected because extending or reducing the growing season impacts cover crop growth.

In the early grazing period, biomass gains from the cover crop were not enough to compensate for establishment and added grazing costs (table 4). Yearly income across regions was still negative but varied between \$2196 and \$5608 when cost assistance was available. Notably, the South West district displayed positive returns even though no

incentives were evidenced for increasing rye populations. While returns were still positive, if rye seeded at 300 plants.m⁻² were early grazed, net income-per acre in south-western IA would be \$1.30 less than if seeded at 150 plants.m⁻².

Additional biomass in the late grazing period would help farmers to save more on feed and pay for the additional cover crop costs. Central West and South West displayed positive changes in yearly income whereas those of North East were again negative (table 5). Net income per year in Central and South amounted to \$5,100 and \$11,600 in the low rye population but positive returns would still be possible without cost-sharing assistance (i.e. \$109 and \$6639). We also found higher returns when rye populations increased, with returns per acre increasing to \$6389 and \$12800. Higher returns per acre suggest that incentives to increase seeding rates would be possible at these locations. In the North East district, on the contrary, evidence of positive margins were evidenced only for the low rye population and when cost-sharing was available (i.e. 278 \$. year⁻¹, 1.40 \$. acre⁻¹). Thus, the less favorable conditions of the Northern districts would suppress incentives for increasing rye populations regardless of the alternatives of support at hand for maize growers.

Harvesting rye biomass would create opportunities for farmers still reluctant to diversify their maize operations. However, additional aspects of rye biomass economics not included in this short-term analysis should be further investigated (Plastina, Liu, Miguez, & Carlson., 2018). First, rye quality forage declines as it matures, so late grazing that favors biomass production might also fail to supply enough feed nutrients, forcing producers to supplement their cattle and raise their production costs. Second, early grazing involves less biomass but allows a grower to enter cattle to graze their fields early in the spring, hence reducing the likelihood of soil compaction (Bergtold et al., 2017). Also, the advantages of rye

in procuring soil benefits occur more commonly in early spring, for which grazing periods should be synchronized such that rye scavenging potential is retained. Lastly, alternative systems that facilitate adaptive management should be also considered when combining maize, cattle production, and cover crops (Franzluebbers & Stuedemann, 2014). For example, maize-for-silage operations would facilitate earlier planting dates that extend the growing season, promoting considerable biomass gains without requiring higher rye populations.

Conclusion

This study complements previous attempts to evaluate cover crop driven effects on maize productivity. As the case of small cereals cultivated for grain, rye cover crop responded positively to increasing plant populations but no indication of an optimum plant population was detected for simulated rye biomass. Biomass as a function of PP was nevertheless moderated by weather and soil conditions, with higher response expected in moderately-drained soils and warmer regions in the US Midwest. The results presented here summarize agronomic scenarios appropriately and provide economic scope for farmers deciding to increase rye PP. When biomass of the cover crop was not utilized, a fall-seeded rye cover crop was still shown to significantly reduce runoff, erosion, and N leaching without penalizing maize yields. When cover crops are grazed, direct benefits can be monetized although incentives for higher rye populations are more likely to occur in districts of Iowa that favor rye growth (Central and South West IA). While the extent of this work is mainly applicable to temperate areas where maize is produced under rainfed conditions during early-fall and late-spring, cover crops pose an alternative to offset environmental externalities common to agricultural systems in other locations in the US upper Midwest.

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Tables and Figures

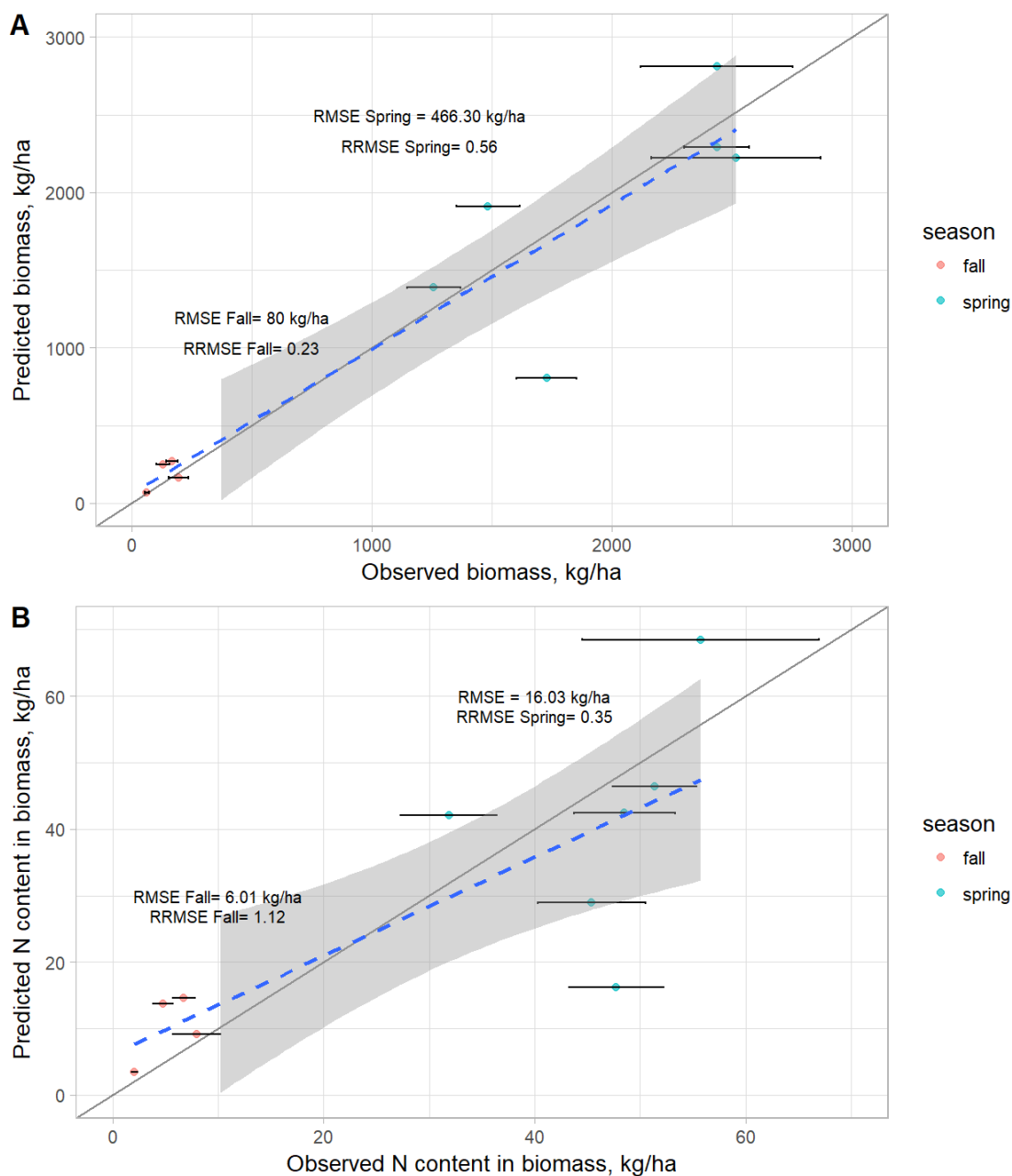


Figure 1. Simulated and observed rye biomass (A) and Nitrogen content in biomass (B) for model validation (2002-2012). Points and horizontal bars are mean and 95% CI for observed biomass and shoot N-content in 8 or 12 replicates per season. Biomass pairs are for cover crops fall -seeded in an odd year and terminated the subsequent spring of an even year (e.g. fall 2001-spring 2002, fall 2003-spring 2004). Data was available for 6 cover crop years.

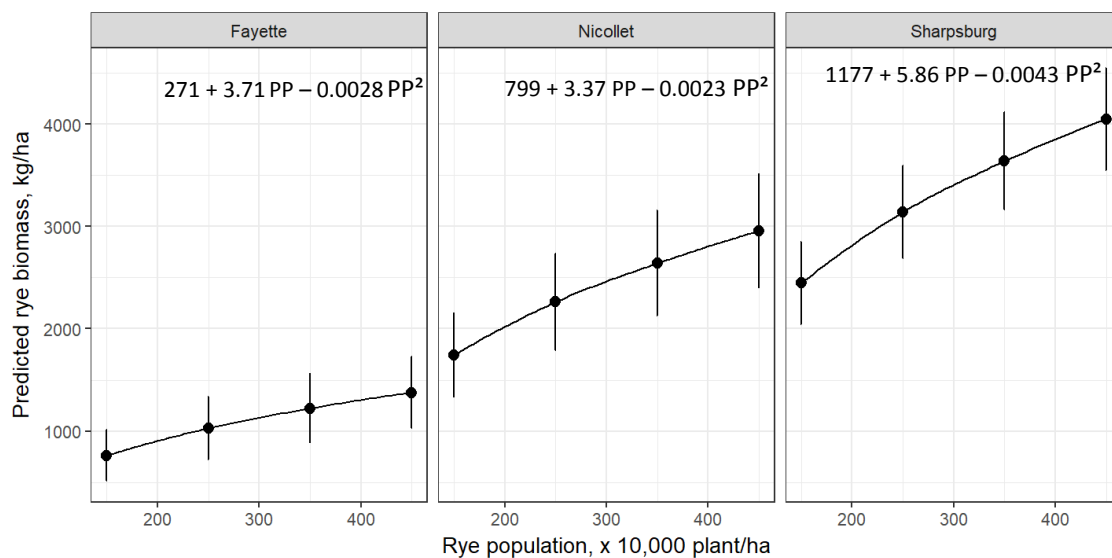


Figure 2. Long-term biomass response to rye population (1990-2015, n=300). Points and vertical bars are 25-year means and 95% CI's for biomass predicted at 4 plant populations (150, 250, 350, 450 plant.m⁻²). Panels are for soil types at three locations in Iowa (Fayette/North East, Nicollet/Central West, Sharpsburg/South West). Soil drainage decreases from high to low in this order: Fayette > Sharpsburg > Nicollet. Intercepts for each regression estimated through the origin (PP=0).

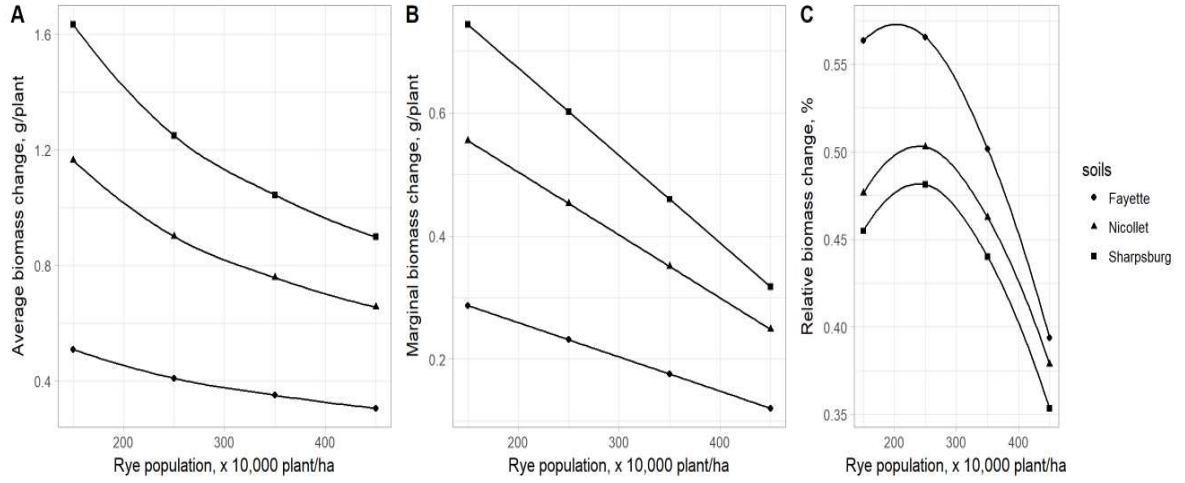


Figure 3. Biomass productivity in response to rye population (1990-2015, n=300). Biomass productivity ratios averaged over 25 years, and computed at 4 plant populations (150, 250, 350, 450 plant.m⁻²). ¹Average, ²marginal, and ³relative change ratios are shown for three soil/locations in Iowa (Fayette/North East, Nicollet/Central West, Sharpsburg/South West). Soil drainage decreases from high to low in this order: Fayette > Sharpsburg > Nicollet.

¹Average change in biomass is $\frac{Biomass [\frac{kg}{ha}]}{PP [\frac{plant}{ha}]}$, calculated from the biomass response curves in figure 2

²Marginal change is $\frac{dBiomass [\frac{kg}{ha}]}{dPP [\frac{plant}{ha}]}$, calculated from the biomass response curves in figure 2.

³Relative change is $(\frac{dBiomass}{dPP}) (\frac{PP}{Biomass})$, or %-rate in biomass per %-increase in PP. Calculated from figure 2.

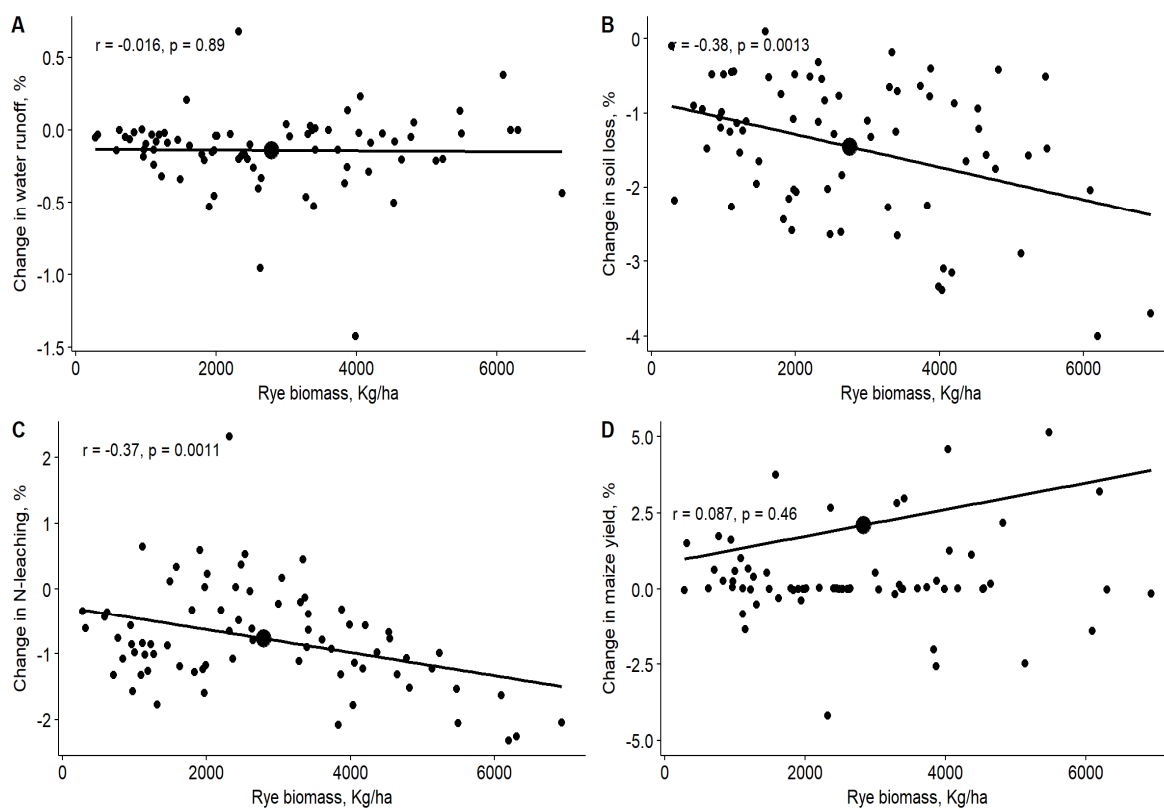


Figure 4. Relationship between maize system outcomes and rye biomass predictions. %-change refers to change in maize indicator with cover crop relative to no cover. %-changes were calculated and combined for three soil/locations in Iowa for 25 years (1990-2015, $n=75$).

Table 1. Crop parameters and soil properties used to run maize-rye simulations in APSIM.

| Soil properties | | | | | | |
|---|---------|------------------------|------------------------|------------------------|------------------------|-------------------------|
| | Depth | Bulk | Lower | Upper | Saturation | K-sat |
| | | Density | Limit | Limit | Limit | |
| | (cm) | (g. cm ⁻³) | (mm.mm ⁻¹) | (mm.mm ⁻¹) | (mm.mm ⁻¹) | (mm.day ⁻¹) |
| Nicollet (North East) (Low drainage) PAW: 310 mm | 0-10 | 1.30 | 0.161 | 0.300 | 0.430 | 100.0 |
| | 10-20 | 1.25 | 0.173 | 0.310 | 0.479 | 100.0 |
| | 20-40 | 1.27 | 0.173 | 0.310 | 0.479 | 100.0 |
| | 40-60 | 1.30 | 0.173 | 0.310 | 0.459 | 100.0 |
| | 60-80 | 1.35 | 0.173 | 0.310 | 0.459 | 100.0 |
| | 100-120 | 1.58 | 0.173 | 0.310 | 0.378 | 1.00 |
| | 120-150 | 1.58 | 0.173 | 0.310 | 0.378 | 0.01 |
| Sharpsburg (South West) (Mid drainage) PAW: 190 mm | 150-180 | 1.58 | 0.173 | 0.310 | 0.378 | 0.01 |
| | 0-10 | 1.35 | 0.211 | 0.336 | 0.441 | 432.1 |
| | 10-20 | 1.35 | 0.211 | 0.336 | 0.441 | 432.1 |
| | 20-30 | 1.35 | 0.213 | 0.337 | 0.441 | 432.1 |
| | 30-40 | 1.35 | 0.213 | 0.337 | 0.441 | 432.1 |
| | 40-70 | 1.37 | 0.231 | 0.346 | 0.433 | 432.1 |
| | 70-90 | 1.37 | 0.231 | 0.346 | 0.433 | 432.1 |
| | 90-120 | 1.42 | 0.175 | 0.314 | 0.433 | 432.1 |
| | 120-150 | 1.42 | 0.175 | 0.314 | 0.414 | 432.1 |

Table 1. Crop parameters and soil properties used to run maize-rye simulations in APSIM (continuation)

| Soil properties | | | | | | |
|--|---------------------------|----------------------------|------------------------|------------------------|------------------------|-------------------------|
| Fayette (High Drainage) PAW: 230 | Depth | Bulk | Lower | Upper | Saturation | K-sat |
| | | Density | Limit | Limit | Limit | |
| | (mm) | (mm.mm ⁻¹) | (mm.mm ⁻¹) | (mm.mm ⁻¹) | (mm.mm ⁻¹) | (mm.day ⁻¹) |
| | 0-10 | 1.40 | 0.171 | 0.311 | 0.422 | 777.8 |
| | 10-20 | 1.40 | 0.171 | 0.311 | 0.422 | 777.8 |
| | 20-50 | 1.35 | 0.169 | 0.310 | 0.439 | 777.8 |
| | 50-60 | 1.35 | 0.169 | 0.310 | 0.439 | 777.8 |
| | 60-70 | 1.35 | 0.169 | 0.310 | 0.439 | 777.8 |
| | 70-90 | 1.35 | 0.169 | 0.310 | 0.439 | 777.8 |
| 90-120 | 1.35 | 0.169 | 0.310 | 0.439 | 777.8 | |
| 120-130 | 1.48 | 0.145 | 0.294 | 0.393 | 777.8 | |
| 130-150 | 1.48 | 0.145 | 0.294 | 0.393 | 777.8 | |
| 150-160 | 1.48 | 0.145 | 0.294 | 0.393 | 777.8 | |
| Crop parameters | | | | | | |
| APSIM id. | Description | Units | Maize | Rye | | |
| [x_tt, y_tt] | Optimum temperature | °C, °C.day ⁻¹ | [26,26] | [18,18] | | |
| [x_tt, y_tt] | Ceiling temperature | °C, °C.day ⁻¹ | [34,34] | [30,30] | | |
| vern_sens | Vernalization sensitivity | unit-less | --- | 5 | | |
| pesw_germ | Soil water - germination | mm.mm ⁻¹ | 0.0 | 0.15 | | |
| y_rue | Radiation efficiency | g. MJ ⁻¹ | [1.60, 1.30] | 1.24 | | |
| leaf_app_rate | Leaf phyllochron | leaf. °C.day ⁻¹ | [57, 32] | 75 | | |
| Planting date | --- | Date | 1-May | 1-Oct | | |
| Harvest/ End | --- | Date | 30-Sep/Ripe | 25-Apr | | |

Table 2. Rye biomass as a function of plant population (n=300). Results for 24 factorial combinations [soil/location (3) x PP (4)] run for 25 years (1990-2015). Biomass and PP transformed to units-per-hectare for clarity. Parameters shown for three soil/locations and standard errors in parentheses.

| Rye Biomass (Kg/ha) | | | | |
|----------------------------|-----------------|--------------------------------------|--------------------|--------------------------------------|
| Soil type | Drainage | Plant population (Plant/ha) | | |
| | | Intercept ($PP=0$) | Linear (PP) | Quadratic (PP^2) |
| Fayette (North East) | High | 271 (41.8) | 3.71 (0.27) | -0.0028 (0.0004) |
| Sharpsburg (South West) | Mid | 1177(93.17) | 5.86 (0.52) | -0.0043 (0.0006) |
| Nicollet (Central West) | Low | 799 (93.17) | 3.37 (0.52) | -0.0023 (0.0006) |
| Random effects | | | | |
| Year (S.D): 994.10 | | | | |
| Residual: 445.60 | | | | |

Table 3. Average APSIM predictions of maize system outcomes. Results are shown by soil and location with and without rye cover crop. Soil types at three locations in Iowa (Fayette/North East, Nicollet/Central West, Sharpsburg/South West).

| Maize system indicator | Soil type | Cover crop | No cover |
|---|-------------------------|------------|----------|
| Nitrate leaching (Kg. NO ₃ .ha ⁻¹ . year ⁻¹) | Fayette (North East) | 5.98 | 20.11 |
| | Sharpsburg (Southwest) | 8.93 | 28.59 |
| | Nicollet (Central West) | 5.97 | 21.96 |
| Cumulative runoff (mm. year ⁻¹) | Fayette (North East) | 141.83 | 163.10 |
| | Sharpsburg (Southwest) | 193.00 | 221.70 |
| | Nicollet (Central West) | 35.33 | 29.16 |
| Soil loss (Mg.ha ⁻¹ . year ⁻¹) | Fayette (North East) | 2.97 | 10.03 |
| | Sharpsburg (Southwest) | 5.27 | 15.86 |
| | Nicollet (Central West) | 0.88 | 2.51 |
| Grain yield (Kg. ha ⁻¹) | Fayette (North East) | 10958 | 10922 |
| | Sharpsburg (Southwest) | 9425 | 9101 |
| | Nicollet (Central West) | 10452 | 10433 |

Table 4. Projected returns for maize farmers using rye as a grazing source in three Iowa districts. Rye value calculated from biomass simulations at two PP. Budgets calculated assuming early grazing (October/25-March/25)

| | Central West | | North East | | South West | |
|--|--------------|---------|------------|---------|-------------|-------------|
| Rye Plant Population (plant. Ha ⁻¹) | 150 | 350 | 150 | 350 | 150 | 350 |
| Cost (\$. ha⁻¹) | | | | | | |
| Rye Establishment | 6956 | 11256 | 6956 | 11256 | 6956 | 11256 |
| Rye Termination (no grazing) | 2424 | 2424 | 2424 | 2424 | 2424 | 2424 |
| Rye additional expenses | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| Income (\$. ha⁻¹) | | | | | | |
| Maize crop impact | 292 | 685 | 332 | 775 | 1373 | 1478 |
| Cost share payment | 5000 | 5000 | 5000 | 5000 | 5000 | 5000 |
| Additional grazing costs (\$. ha⁻¹) | | | | | | |
| Rye Termination | 0 | 0 | 0 | 0 | 0 | 0 |
| Additional labor - cattle-grazing | 206 | 206 | 206 | 206 | 206 | 206 |
| Additional investments for grazing | 1611 | 1611 | 1611 | 1611 | 1611 | 1611 |
| Additional Income of grazing (\$. ha⁻¹) | | | | | | |
| Value of feed replaced by rye biomass | 2578 | 5084 | 1244 | 2613 | 4880 | 8818 |
| Net income/year (maize only) ¹ | (5088) | (8995) | (5048) | (8905) | (4007) | (8202) |
| Net income/year (maize + rye grazing) ² | (1903) | (3304) | (3197) | (5608) | 1479 | 1222 |
| Net income/year (maize + rye grazing)/ No cost share ³ | (6903) | (8304) | (8197) | (10608) | (3521) | (3778) |
| Net income/acre (maize only) | (25.44) | (44.97) | (25.24) | (44.52) | (20.04) | (41.01) |
| Net income/acre (maize + rye grazing) | (9.51) | (16.52) | (15.99) | (28.04) | 7.39 | 6.11 |
| Net income/acre (maize + rye grazing)/ No cost share | (34.51) | (41.52) | (40.98) | (53.04) | (17.60) | (18.89) |

¹Net Income (maize only) = (Maize crop impact + cost share payment) – (cost rye establishment + cost rye termination + rye additional expenses)

²Net Income (maize + rye grazing) = (Maize crop impact + cost share payment + income grazing) – (cost rye establishment + rye additional expenses) – (additional costs labor grazing + additional investments for grazing)

³Net Income (maize + rye grazing/No cost share) = Net Income (maize + rye grazing) – cost share payment

Table 5. Projected returns for maize farmers using rye as a grazing source in three Iowa districts. Rye value calculated from biomass simulations at two PP. Budgets calculated assuming late grazing (November/15-April/15)

| | Central West | | North East | | South West | |
|--|--------------|---------|-------------|---------------|------------|---------|
| Rye Plant Population (plant. Ha ⁻¹) | 150 | 350 | 150 | 350 | 150 | 350 |
| Cost (\$. ha⁻¹) | | | | | | |
| Rye Establishment | 6956 | 11256 | 6956 | 11256 | 6956 | 11256 |
| Rye Termination (no grazing) | 2424 | 2424 | 2424 | 2424 | 2424 | 2424 |
| Rye additional expenses | 1000 | 1000 | 1000 | 1000 | 1000 | 1000 |
| Income (\$. ha⁻¹) | | | | | | |
| Maize crop impact | 292 | 685 | 332 | 775 | 1373 | 1478 |
| Cost share payment | 5000 | 5000 | 5000 | 5000 | 5000 | 5000 |
| Additional grazing costs (\$. ha⁻¹) | | | | | | |
| Rye Termination | 0 | 0 | 0 | 0 | 0 | 0 |
| Additional labor - cattle-grazing | 206 | 206 | 206 | 206 | 206 | 206 |
| Additional investments for grazing | 1611 | 1611 | 1611 | 1611 | 1611 | 1611 |
| Additional Income of grazing (\$. ha⁻¹) | | | | | | |
| Value of feed replaced by rye biomass | 9591 | 14782 | 4720 | 7476 | 15040 | 20373 |
| Net income/year (maize only) ¹ | (5088) | (8995) | (5048) | (8905) | (4007) | (8202) |
| Net income/year (maize + rye grazing) ² | 5109 | 6389 | 279 | (1266) | 11639 | 12778 |
| Net income/year (maize + rye grazing)/ No cost share ³ | 109 | 1389 | (4721) | (6266) | 6639 | 7778 |
| Net income/acre (maize only) | (25.44) | (44.97) | (25.24) | (44.52) | (20.04) | (41.01) |
| Net income/acre (maize + rye grazing) | 25.55 | 31.95 | 1.39 | (6.33) | 58.19 | 63.89 |
| Net income/acre (maize + rye grazing)/ No cost share | 0.55 | 6.95 | (23.60) | (31.33) | 33.2 | 38.89 |

¹Net Income (maize only) = (Maize crop impact + cost share payment) – (cost rye establishment + cost rye termination + rye additional expenses)

²Net Income (maize + rye grazing) = (Maize crop impact + cost share payment + income grazing) – (cost rye establishment + rye additional expenses) – (additional costs labor grazing + additional investments for grazing)

³Net Income (maize + rye grazing/No cost share) = Net Income (maize + rye grazing) – cost share payment

Appendices

Table A1. Appendix. Maize yields and rye biomass simulations used for the economic analysis (SI-units)

| District | Maize | | | Winter rye | | Winter rye | |
|-----------------|-----------------------|----------------------|-------------------------|-----------------------------------|----------------------|---------------------------------|----------------------|
| | Seed density | Expected Yield | Expected Δ Yield | Early grazing: (Oct-25/Mar-25) | | Late grazing (Nov-15/Apr-15) | |
| | | | | Fall Biomass | Spring Biomass | Fall Biomass | Spring Biomass |
| | plant.m ⁻² | kg. ha ⁻¹ | % | Kg. ha ⁻¹ | kg. ha ⁻¹ | Kg. ha ⁻¹ | kg. ha ⁻¹ |
| IA Central West | 150 | 9519 | 0.3 | 28 | 292 | 66 | 1143 |
| IA Central West | 350 | 9566 | 0.7 | 65 | 577 | 149 | 1715 |
| IA North East | 150 | 10842 | 0.3 | 25 | 132 | 53 | 543 |
| IA North East | 350 | 10848 | 0.7 | 59 | 271 | 120 | 823 |
| IA South West | 150 | 10332 | 1.3 | 32 | 584 | 85 | 1812 |
| IA South West | 350 | 10306 | 1.4 | 74 | 1038 | 191 | 2379 |

Table A2. Appendix. Maize yields and rye biomass simulations used for the economic analysis (imperial-units) as required by the cover crops economics decision tool.

| District | Maize | | | Winter rye Early grazing (Oct-25/Mar-25) | | Winter rye Late grazing: (Nov-15/Apr-15) | |
|--------------------|-------------------------|------------------------|-------------------------|--|------------------------|--|------------------------|
| | Seed density | Expected Yield | Expected Δ Yield | Fall Biomass | Spring Biomass | Fall Biomass | Spring Biomass |
| | plant. ft ⁻² | Bu. acre ⁻¹ | % | lb. acre ⁻¹ | lb. acre ⁻¹ | lb. acre ⁻¹ | lb. acre ⁻¹ |
| IA Central West | 16 | 152 | 0.3 | 25 | 265 | 59 | 1020 |
| IA Central West | 33 | 153 | 0.7 | 58 | 514 | 133 | 1530 |
| IA North East | 16 | 173 | 0.3 | 23 | 117 | 47 | 484 |
| IA North East | 33 | 173 | 0.7 | 52 | 242 | 107 | 734 |
| IA South West | 16 | 165 | 1.3 | 28 | 521 | 76 | 1616 |
| IA South West | 33 | 165 | 1.4 | 66 | 926 | 170 | 2122 |

Table A3. Appendix. Seeding rates and costs estimated for the economic analysis.

| Plant population | Plant population | Seed density | Seed cost ^{1,2,3} |
|-----------------------|-------------------------|------------------------|----------------------------|
| plant.m ⁻² | plant. ft ⁻² | lb. acre ⁻¹ | \$. acre ⁻¹ |
| 150 | 16 | 49 | 19.6 |
| 350 | 33 | 103 | 41.1 |

¹ Seeding fixed costs based on \$0.40 per pound of commercial seed.

² Commercial seed is usually sold in 25 to 40-lb bags priced at \$10 to \$ 12.50 per bag by local suppliers.

³ Rye populations in plants.m⁻² were brought to plant. ft⁻² and transformed to a weight-seed basis (lb. seed. acre⁻¹). Rye seeding rates (i.e. PP) were also adjusted for 93% purity and 3% mortality, assuming 1000 viable kernels in 33 g. of pure seed.

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CHAPTER 4. IMPROVED REPRESENTATION OF WINTER COVER CROPS: MODELING PHENOLOGY AND BIOMASS OF CEREAL RYE IN IOWA

A paper to be submitted to *Agronomy Journal*

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Abstract

Accurate model representation of growth and development patterns are needed for assessing cover crop effects at the field level. At their current state, however, it is still uncertain whether crop simulation systems can effectively capture phenology and growth of cereal cover crops. We adapted APSIM – a widely utilized agronomic model- to simulate rye (*Secale cereale* L.) established as a winter cover crop between phases of a maize-soybean rotation in Iowa and used field observations to improve phenology and biomass predictions. First, we regressed rye leaf stages against thermal time using three different methods to quantify phyllochron changes within the cover crop season. Phyllochron rates differed significantly between the fall and spring periods yet showed high sensitivity to the thermal scale utilized (range: [60 – 120] GDD.leaf⁻¹, for fall and spring respectively). Also, we conducted a sensitivity analysis and additional calibration to identify parameters in APSIM with the highest probability of influencing growth stage and biomass predictions.

Accordingly, 65% variation in predicted growth stage was explained by changes in cultivar-specific parameters referring to thermal time elapsed from sowing to the end of the vegetative period. Rye biomass simulations were overall more responsive than phenology to changes in selected parameters, yet 50% of its variability was driven by minimum soil moisture required for germination and establishment. While proper phenological calibration can reduce uncertainty in field-scale predictions of cover crop biomass, mechanistic models can be enhanced by bringing a more active contribution of inter-seasonal phyllochron responses.

Introduction

Cover crop adoption among US growers has increased considerably in the last years. Total area planted to cover crops in Iowa has grown from 100,000 to 350,000 acres between 2012 and 2016 whereas 43% of the 4 million acres of all cover crops planted nationwide by 2014 were located in the US Midwest (Arbuckle & Roesch-McNally, 2015; Dunn, Prokopy, Myers, Watts, & Scanlon, 2016; Plastina et al., 2018). Based on farmer surveys, frequent cover crop users are said to be planting twice the number of acres they were in 2011 (CTIC, SARE, & ASTA, 2016). Besides federal support programs for frequent and first-time users, recent increases in cover crop adoption have also resulted from the efforts of researchers, extension, and farmer groups, who assist growers in planning strategically to overcome the inherent challenges of establishing a cover crop.

Cover crops can be part of pure or mixed stands of annual, or perennial species, covering cropland for parts or all of the year (Altieri, 1997). The time of the year where winter cover crops are grown, however, determines sub-optimal conditions for crop growth (Thorup-Kristensen, Magid, & Jensen, 2003). Thus, the short period between grain harvest

and cover crop planting makes growers in the upper-corn belt to rely mostly on winter-hardy small grains. Cover crop development may respond differently to the progressive reduction in air temperatures that follow planting in the fall, and separation between vegetative and reproductive stages depend on environmental factors other than temperature (e.g. vernalization, photoperiod) as planting is delayed in northerly areas. Also, cereal cover crops provide soil and water protection, and given the right management and weather conditions, their benefits could be maximized during the vegetative period. In fact, cover crop biomass has been shown to increase weed control or protection against soil erosion but it is highly dependent on successful establishment and weather conditions.

Biomass production of cover and harvestable crops is linked in addition to phenological events. Phenology is the chronological succession of morphological events that complements crop expansion and growth, and in the context of cover crops, can be useful to monitor processes with direct impact on subsequent cash crops. Phenology, for example, can be helpful in assisting growers to make the right management choices in cover crop systems, such as planning optimal termination dates for winter rye before corn (Mirsky et al., 2009) , or evaluating rye termination influence on soil water and N status (Krueger, Ochsner, Kantar, Sheaffer, & Porter, 2010) . As important as it is in assisting farm scheduling, phenology also forms the basis of computer assisted tools that simulate cover crops and their responses across multiple environments and management scenarios. Therefore, improving the current knowledge about development and phenological patterns of overwintering cereals, currently missing in the cover crop literature, will help capture site and yearly differences for a more effective simulation of cover crop outcomes at the field scale.

Computer simulation models can be valuable tools in assessing cover crop effects on soil and crop production. To this effect, cover crops have been modeled by creating ad hoc tools adapted for a problem in particular or by adapting more general agronomic decision systems. Examples of the first are two mechanistic models developed by Feyereisen et al. (2006) and Baker & Griffis (2009). These models simulate rye growth to explore the suitability of winter rye as an N catch crop or as a potential source of biomass for the biofuel industry. Because these models were developed for specific goals, some components were more favored than others; for example, by describing soil hydrological relationships in detail while keeping phenological descriptions at a minimum. In a broader context, however, thorough evaluations of rye cover crops across multiple scenarios require computer tools that integrate multiple levels of detail. Further, the principles of growth and development are akin to multiple species, so time and effort can be saved by adapting such general decision tools in the assessment of maize-soybean rotations that include a rye cover crop. To accomplish this, however, robust procedures are needed to ensure satisfactory representation of a winter cover crop.

Here, we aim to enhance the capabilities of a widely used simulation system to represent winter cover crops. No previous study to our knowledge has evaluated such inquiries in the context of winter rye adapted as a cover crop in a temperate region. Winter rye (*Secale cereale* L.) was chosen because it is a prevalent species among growers due to its winterhardiness and ability to resume growth in spring (Kaspar & Bakker, 2015; Kladvko et al., 2014; Ramirez-Garcia, Gabriel, Alonso-Ayuso, & Quemada, 2015). While simulation systems have been used to simulate cover crop effects on soils and cash crop yields (Basche et al., 2016; Dietzel et al., 2016; Martinez-Feria et al., 2016; Salmeron et al., 2014), more

careful descriptions of the agronomic and physiological relationships involved in establishing rye cover crops are needed.

We collected field observations from two Iowa long-term cover crop trials and use statistical methods to improve phenological characterization and biomass predictions of a rye cover crop in a widely used simulation system (APSIM). Specifically, we propose to: 1) Quantify leaf development (i.e. phyllochron rates) of a fall-seeded rye cover crop in response to temperature; 2) Identify model parameters in APSIM to which phenology and biomass of the rye cover crop are most sensitive; and 3) Calibrate and validate a modified rye module in APSIM against fall and spring biomass records collected in central Iowa. This study is focused on maize and soybean rotations including a broadcast-seeded rye cover crop, but its results are applicable to temperate regions where cover crops, especially small grains, grow during cold and short-days in the winter season.

Materials and Methods

Site description and data. The Kelly experimental farm (42.05N, 93.71W) and the Iowa State University Agricultural and Engineering Farm-ISUAG (42.02N, 93.76W) included cover crop treatments evaluated for their impacts on maize and soybean systems. Soil types at both sites are predominantly fine loamy and moderately well-drained, characteristic of the Northern Iowa region. Experimental plots were no-till managed and included a cover crop treatment, either established after maize or soybean (Kelly), or including both phases of the rotation in the same year (ISUAG). Rye cover crops were broadcast-seeded into standing cash crops via low-impact/high-clearance equipment at Kelly but were hand-seeded into smaller plots at ISUAG. Rye populations close to 3.75 and 4.75 x 10⁶ seeds. ha⁻¹ were targeted at Kelly and ISUAG in view of the different seeding methods

per site. Because rye at Kelly was terminated at a single date, only plots terminated 15 days before maize or soybean were chosen at ISUAG to ensure data consistency across sites.

Further details about field management and research at Kelly can be found in Kaspar, Jaynes, Parking, Moorman, & Singer (2012), and Basche, et al. (2016). Treatment descriptions for the ISUAG termination trials are reported in Craft (2017).

Plant populations and ground cover are important indicators of cover crop establishment. Also, plant population is a major input determining canopy size and biomass accumulation in APSIM, and hence, it was measured to represent actual establishment of the cover crop in future simulations. Plant populations (plant.m^{-2}) were evaluated on 12 grids, 10-th of a square-meter each, placed along middle rows left by the previous cash crop. Viable rye seedlings in the fall were counted 21 days after seeding and counted again the day before cover termination. Ground cover (%), defined as the fraction of the ground covered by the rye canopy, was estimated also twice in the growing season: October-21 and April-22 of consecutive years. Twenty-four randomly chosen areas in a plot, 1 m^2 each, were photographed, and processed digitally to estimate green areas (Patrignani & Ochsner, 2015).

Rye phenology was recorded by identifying plant morphological changes described by the Hauns and Zadoks numerical systems (Haun, 1973; Zadoks, Chang, & Konzak, 1974). Leaf stages (Hauns) of ten plants, tagged and identified within a recurrent sampling area, were monitored weekly between seeding and termination of the cover crop in 2016 and 2017. Zadok stages were recorded on a weekly basis by randomly selecting 10 different plants from each plot for two years (2015/2016-2016/2017). Phenology was collected at two scales for a different purpose. Hauns were regressed against thermal time to estimate phyllochron rates

whereas Zadoks were used to calibrate phenology of the fall-seeded rye cover crop in APSIM.

Thermal time and rye phyllochron. Weather data was obtained from two sources: daymet (Daymet., 2016), and the Iowa environmental Mesonet (Iowa Mesonet., 2016). Three thermal time methods were defined considering temperature values where crops have been shown to develop at different rates (Archontoulis, Miguez, & Moore, 2014). The first two methods refer to the summation of growing units above a base temperature and without upper bounds, namely, 0 degree Celsius (0B) or four degrees Celsius (4B). Both 0 and 4 °C are the two most commonly reported base temperatures in the literature for rye and similar winter cereals. Linear methods are commonly used because of their simplicity and adaptability to model crop development during the summer season (Kumudini et al., 2014), however they do not account for daylength or vernalization (Cao & Moss, 1991; Saiyed, Bullock, Sapirstein, Finlay, & Jarvis, 2009); effects known to modulate development rate of long-day cereals. To account for these effects, we included the mechanistic algorithm embedded in APSIM, which models crown thermal time (i.e. thermal time experienced at the basal mass of tissue where leaf differentiation takes place). Crown thermal time (CTT) in APSIM resembles the concept of physiological days, meant to depict a decline in development response beyond an optimal temperature (Sands, Hackett, & Nix, 1979). Thermal time was computed as follows:

$$GDD = \begin{cases} T_m - b & T_m \geq T_b \\ 0 & T_m < T_b \end{cases} \quad \text{Equation (1)}$$

$$CTT = \begin{cases} T_m, & 0 < T_m < 25 \\ \beta_1 T_m, & 25 < T_m \leq 30 ; \\ 0, & T_m \leq 0 \cup T_m > 30 \end{cases} \quad \beta_1 < 0 \quad \text{Equation (2)}$$

T_m is the average between daily minimum and maximum temperatures, and parameter b in equation 1 was set to 0 or 4 °C (i.e. 0B or 4B). Daily average temperatures in the APSIM crown algorithm (APSIM-AC) are mapped onto crown thermal time (CTTs) at a constant rate until 25 °C, after which a decreasing rate is controlled by parameter β_1 (equation 2).

APSIM-AC is flexible enough to accept critical temperatures for crop development beyond a single value, allowing a user to interpolate multiple thermal response curves if a default set of coordinates are modified. The cereal module we utilized (APSIM-wheat) recognizes a single optimal temperature (i.e. 25 °C) that agrees well with values reported by field and laboratory experiments of winter cereals at several thermal regimes (Porter & Gawith, 1999). APSIM-AC additionally discounts CTTs by effects of geodesic relationships relative to time of the year and latitude (daylength) and empirical adjustments for cold requirements before flowering (vernalization). Graphical representations of each method are shown in figure 1, and specific details about photoperiod and vernalization equations can be found in the APSIM-wheat official documentation (Zheng, Chenu, Doherty, & Chapman, 2014).

Finally, rye GDDs and CTTs were accumulated daily between cover crop seeding and termination (September-9/2016-May 8/2017). Haun stages from both locations were combined and regressed against thermal time from each method. By comparing regressions from three thermal methods, we visualized development patterns predicted by APSIM and what a typical cover crop displays under field conditions. As such, three regression models without intercept were run, each including GDD as a continuous variable plus its interaction with season (fixed-effects term). Phyllochron rates for the cover crop were estimated as the reciprocal of the slope in each regression ($\text{GDD} \cdot \text{leaf}^{-1}$, $\text{CTT} \cdot \text{leaf}^{-1}$), and a different effect

between seasons was deemed significant if fall and spring slopes differed statistically from zero at the 0.01 level.

Sensitivity analysis of the rye model. A global sensitivity analysis was conducted to assess phenology and biomass changes of the cover crop as driven by parameter variation in APSIM. Three major steps were followed: 1) determine parameter sets, 2) run APSIM at each parameter combination; and, 3) quantify the amount of variation in model outputs due to individual changes in parameters. First, we generated 1500 samples where a selected parameter took on a single realization of a random distribution. Parameters were assumed uniformly distributed and bounded within $\pm 50\%$ perturbation around its default value (table 1). After running APSIM at each parameter sample, model outputs were stored separately and modeled as linear functions of the parameters via GAMS (generalized additive smoothers). Linearizing dynamic complex models via emulators extends correlation or regression methods by capturing possible non-linear effects among parameters and offers computational advantages relative to other algorithms for global sensitivity analysis, such as SOBOL or FAST (Stanfill, Mielenz, Clifford, & Thorburn, 2015). Generally speaking, total variability in model outputs can be decomposed into individual sources after running a linearized version of a process-based model. Individual measures of parameter-driven variability in the model are computed as ratios given by each parameter variance and its interactions divided by total variance in the model (Monod, Naud, & Makowski, 2006). If $Y(\cdot) = f(\mathbf{x}) + \epsilon$ denote the GAMS fitted version of APSIM, variances attributed to the i -th parameter \mathbf{x} , and any (i,j) -th parameter interaction, can be defined as $V_i = \text{var} [E(Y|\mathbf{x}_i)]$ and $V_{ij} = \text{var} [E(Y|\mathbf{x}_i, \mathbf{x}_j)]$. Sensitivity indexes were computed as ratios of the form $S = V/\text{Var}(Y)$, and total sensitivity in growth stage or biomass of the cover crop was simply the

proportion that remained after removing main and high-order interaction effects of a parameter, i.e. $(1 - S)$. Twelve parameters with potential to influence phenology and biomass of the cover crop through shoot-root mechanisms were selected for sensitivity analysis (table 1); some of which have been reported to affect cereals under different environments and conditions (Mohanty et al., 2012; Zhang, Feng, Wang, Wang, & Li, 2012).

Rye modeling: calibration and validation. APSIM is a simulation support system that integrates rules for management decisions affecting crop production. Limited primarily by environment factors, crop growth is modeled as the result of resource capture and transformation in response to temperature, solar radiation, water, and N supply. APSIM is built-upon a central engine where different climate, soil, and plant processes are independently integrated to run crop simulations at a daily time step (Keating et al., 2003). Because a rye module is currently unavailable in APSIM, the American winter wheat “yecora” was chosen to simulate development and growth of a fall-seeded cover crop. APSIM-wheat inherits universal principles of crop response from a standard plant module where specific properties of the cover crop (i.e. parameters) can be modified to simulate cropping scenarios across one or multiple environments.

Phenology is represented by ten phases limited by thermal time accumulation, except pre-emergence, which is controlled by soil water. Vernalization and photoperiod effects are cultivar specific and accounted from emergence to anthesis. If soil nutrients are plentiful, biomass is the result of radiation interception and conversion, being limited further by water stress if water demand is higher than water supply. Phenology and biomass are linked; therefore, adequate calibration of the model is needed for more effective biomass partition across different crop organs.

Based on results from the sensitivity analysis, we performed a calibration method on those parameters whose sensitivity indexes were 0.25 or above (i.e. $\geq 25\%$ variability in model outputs explained by the parameter). Literature searches and expert opinion were preferred for less influential parameters. Also, calibration was performed sequentially, beginning with phenology (Zadoks) and continuing later with biomass.

Because the calibration dataset was small we followed a two-fold calibration and testing approach, splitting the data in two sets: year one (2015-2016) and year two (2016-2017). At the same time, an iterative process was implemented to run APSIM at small incremental steps of the parameter of interest such that error between model predictions and observations was minimized. Estimation and tests were performed on both data splits simultaneously, or in other words, the parameter was estimated in one split, assigned to APSIM at such a new value and tested against observed data in the other split. Final value for the parameter of interest was chosen as the one that reduced test error the most.

Finally, APSIM was calibrated at the new estimated values and validated against observed biomass at the Kelly station; combining fall and spring records of rye planted between maize and soybean phases in the 2012-2015 period. The metrics used for model calibration and evaluation were the relative mean squared error (RMSE) and root relative mean squared error (RRMSE), with lower values meaning better match between observed and simulated values.

All the statistical procedures were implemented under the R-statistical environment (R v.3.4). For sensitivity analysis we followed the steps of the GAM single algorithm proposed by Stanfill, Mielenz, Clifford, & Thorburn (2015) and the procedures for fitting generalized linear models outlined in James, Witten, Hastie & Tibshirani (2016). Calibration

and validation methods were implemented as recommended by Wallach, Makowski, Jones & Brun (2014). Functions available in the libraries *apsimr*, version 1.2 (Stanfill, 2015), *gam*, version 1.15 (Hastie, 2018), and *xml*, version 3.98 (Temple, 2018), were used for file manipulation and improved data communication between R and the APSIM model.

Results and Discussion

Total rainfall in November 2015 was 220 and 166 mm at Kelly and Isuag respectively. This difference was due to the additional week elapsed since cover crop planting at Kelly and carried on for much of the season until cover crop termination (April-2016). Because of the similar seeding dates in year two (i.e. August 26-29, 2016), total rainfall between sites was not significantly different. Overall, however, 2015 and 2016 were markedly wetter years compared to the 20-year averages estimated for central Iowa. Thermal accumulation (GDD) is further discussed in subsequent sections on rye development.

Rye populations showed a persistent reduction between fall and spring of both years (table 3). Rye populations decreased from 228 [(180, 274), 95% CI] to 184 [(160,207), 95% CI] plants.m⁻² at Kelly, which amounted to a 19% decrease over the 2015-2016 cover crop season. Similarly, rye populations at Isuag decreased from 258 to 155 plants.m⁻² (-55%) over the same period. These patterns were evident also in year two, where plant density reductions between fall and spring added up to 40 and 55% at both sites. Establishment in terms of ground cover, on the other hand, showed no signs of a fully developed canopy by the cover crop in either year or site of the study. Ground cover ranged between 2 % [(1, 4), 95% CI] and 32 % [(25, 41), 95% CI] in 2015-2016, and 56% [(54, 69), 95% CI] in spring of 2017.

Leaf stages were similar between sites. Development trends in the 2016-2017 cover crop season were similar regardless of the different sampling dates at each site, with ISUAG

being always ahead because of the earlier seeding date. On average, final Haun stage in the fall was between 5 and 6, indicating a fully vegetative cover crop. After the dormancy period, the first significant change in leaf stage occurred in March 24, where plants at either site displayed an additional leaf relative to the fall (Haun 7 to 8). Rye leaf rate after April 2017 increased at a faster rate, reaching Haun 9 to 10 by early May, i.e. flag leaf, or the 4th leaf developed after node jointing, visible at the top. In general, rye cover crops in Iowa growing between September and May of consecutive years are likely to reach: 1) full vegetative status (Haun 5 to 6) before winter dormancy; and, 2) Pre-reproductive stage (Haun 9 to 10) before spring termination.

Thermal accumulation between September 2016 and May 2017 varied across scales (figure 2). Thermal time in the 0B-Model added up to nearly 900 GDD before the overwintering period (Oct-24) and 1800 GDD before cover crop termination. Increasing the minimum base parameter from 0 to 4 °C (4B-Model) limited thermal accumulation between 750 and 1250 GDD over the same period. The mechanistic approach (APSIM-AC) limited thermal time between fall and spring to nearly 500 and 1250 CTT (i.e. physiological-days). It can be seen that the more restrictions are imposed on a thermal time algorithm, the fewer thermal units accumulate over a time period, i.e. downward shifts in the cumulative thermal curves shown in figure 1. Furthermore, CTT carries photoperiodic and vernalization adjustments onto thermal accumulation. Because of the mechanisms involved, the phyllochron estimates from each method are not directly comparable (i.e. GDD vs CTT), but evidenced different development patterns between seasons.

Regression slopes in the scatters between Haun stages and thermal time (GDD) were significantly different in the fall and spring of the 2016-2017 period ($p < 0.05$, table 4, figure

3). The simple thermal time methods (0B and 4B) displayed fall phyllochron rates between 120 and 160 GDD.leaf⁻¹, implying that the cover crop would require this many GDDs to develop leaves before dormancy. Phyllochron in spring decreased to 80 and 125 GDD.leaf⁻¹, suggesting faster leaf appearance following the dormancy period.

Consistent with our results, phyllochron differences within a growing season have been reported for rye and other overwintering species. Oakes, Heiniger, Crozier, Murphy, & Wilkerson (2016), and Juskiw, Jame, & Kryzanowski (2001) found phyllochron ranges between 82 and 128 GDD.leaf⁻¹, and 40 to 108 GDD.leaf⁻¹, for winter wheat and spring barley adapted to short growing seasons in North Carolina or Alberta (CAN). Likewise, Gan & McLeod (1997) showed phyllochron evolving at different rates for pre and post-vernalized winter rye ($\approx [60, 150 \text{ GDD.leaf}^{-1}]$), evidencing that separate responses exist during the pre and post dormancy growing periods. Phyllochron estimated from APSIM-AC also evidenced different responses for rye development across seasons. Rye phyllochron was 50 and 127 CTT.leaf⁻¹, which compares fairly well relative to development rates of winter wheat estimated via thermal time controlled by cardinal temperatures and photoperiod (Saiyed et al., 2009).

Few studies have contrasted the effect of different ranges of thermal response in cereal phenology. Overall, thermal functions that include richer physiological descriptions (e.g. APSIM-AC) have been shown to outperform empirical equations at supra-optimal temperatures because most of the data from which they are derived is generated from controlled conditions (Parent, et al., 2010). Empirically driven equations (e.g. 0C-4C) are derived from data with little or none supra-optimal temperatures (Stewart, Dwyer, & Carrigan, 1998), hence, are more sensitive to low or high extreme temperatures and would

describe leaf rate more efficiently within optimal ranges for cereal development. A more rigorous examination of rye phyllochron sensitivity to different temperature ranges was not possible because of our small dataset, but future work for wheat, rye, or other winter cereals is encouraged. Kumudini et al., (2014), for example, implemented an inter-comparison of 8 thermal response functions for maize, finding consistent variability ranges in phenological predictions (CV= 6-10% thermal units) and different sensitivities to temperature changes depending on the mechanistic description of the thermal equations employed.

Rye sensitivity analysis in APSIM. Different parameter sensitivities were detected for growth stage (Zadoks) and biomass (kg. ha^{-1}) of a fall-seeded rye cover crop simulated in APSIM (figure 4). The initial runs of the model ($n=1500$) allowed for simulating a representative number of parameter combinations produced by the MonteCarlo sampling procedure. Total sensitivity indexes were estimated between 0.0 and 0.68, indicating that zero to sixty-eight percent variation in model outputs of the cover crop would likely be explained by variation in one of the selected parameters. Specifically, three cultivar specific parameters were found to be largely influential on rye stage predictions: thermal time to juvenile ($s=0.68$, $\text{CV}=0.30\%$), thermal time to flowering initiation ($s=0.17$, $\text{CV}=2.02\%$), and sensitivity to photoperiod ($s=0.14$, $\text{CV}=2.47\%$). Contrary to our expectations, leaf phyllochron accounted for almost zero percent variation in cover crop Zadoks stage but affected slightly rye biomass predictions ($s=0.04$, $\text{CV}=23.4\%$). Along the same lines, biomass simulations of the cover crop were predominantly sensitive to minimum soil moisture for germination, explaining half of variation in biomass outputs ($s=0.51$, $\text{CV}=1.52\%$), thermal time to juvenile ($s=0.29$, $\text{CV}=3.19\%$), and to a lesser extent, sensitivity to vernalization ($s=0.10$, $\text{CV}=5.60\%$). Overall, rye biomass was more sensitive to the

selected parameters than phenology, with parameters that control shoot and root expansion displaying sensitivity indexes between 0.04 and 0.20, e.g. root rate of elongation ($s=0.04$, $CV=22.19\%$), or initial leaf area per plant ($s=0.20$, $CV=4.68\%$).

Rye Zadoks sensitivity to degree days to flowering, end of vegetative, and photoperiod, evidenced the thermal processes embedded in APSIM to describe plant development. Because thermal caps are cultivar specific and are parametrized in APSIM as such (Zheng et al., 2014), a large variability was therefore expected when testing a large pool of thermal variation in the sensitivity analysis (i.e. $\pm 50\%$ perturbation around default parameter values). In line with our results, sensitivities to thermal time for vegetative and flowering completion have been reported for different crops and conditions. For example, Ahmed et al., (2016) showed that wheat flowering time was controlled by thermal time to initiation, and Alderman & Stanfill (2017) estimated that between 50 and 60% of variation in spring wheat phenology resulted from cultivar specific parameters related to heat accumulation.

Likewise, the significant influence of thermal accumulation from sowing to juvenile, and sowing to flowering initiation of the cover crop, would support the findings from Casadebaig et al., (2016) and Zhao, Bryan, & Song (2014), who quantified variations in flowering occurrence in response to wheat cultivar traits related to heat accumulation; albeit these authors caution about possible changes in sensitivity results if management, or environmental conditions in the analysis change, e.g. nitrogen or water stress. In our field study, for instance, rye was broadcast-seeded, and as such, the high biomass sensitivity to soil water content may reflect an altered seed-soil environment that affects germination and establishment of the cover crop. Besides physical factors that may or may not be fully

captured by the model, e.g. standing maize or soybean canopies at cover planting, seed predation, seed purity, etc., germination of broadcast-seeded rye becomes more dependent on top soil moisture than drilled or incorporated cover crops and is favored by rainfall events in the days following planting (Brennan & Boyd, 2012; Wilson, Baker, & Allan, 2013).

Vernalization was found to influence biomass predictions only slightly, although APSIM does account for its effects since emergence until flower initiation. Such a minimum influence, in contrast to much larger effects reported for winter wheat (McMaster, 2003), stems from the limited growing season of the cover crop, exacerbated by the fixed planting date that we assumed to simplify the iterative runs of the model during the sensitivity analysis. Further replication of this study might benefit from simulating multiple planting dates, where vernalization effects on extending or shortening the vegetative period, as well as LAI expansion and biomass accumulation, can be more thoroughly evaluated.

Rye model calibration and validation. Initial runs of the model resulted in poor agreement with respect to observed phenology and biomass (figures 5 and 6). Crop stages (Zadoks) of broadcast-seeded rye were over-predicted by 64% (RRMSE= 0.64) relative to field observations of two cover crop seasons (2015/2016-2016/2017). Also, the length of the dormancy period was modeled too short, with cover crop going dormant by November and resuming growth early in January next year. Similarly, biomass was severely over-predicted during the pre-calibration phase of the rye cover crop (i.e. wheat module), with overall departures of 3900 kg. ha⁻¹ (RMSE = 3900), or 2.6 times the average of field recorded biomass during the same period (RRMSE= 2.66). Panels A and B in figure 5 illustrate the correspondence between cover crop status and biomass, which confirms the need for calibrating phenological parameters to reduce biomass overprediction.

As expected, model agreement for cover crop stages improved after model calibration (figure 7). RMSE and RRMSE were reduced to 3.79 Zadoks and 16% respectively. Fall mean stage was predicted at 21 Zadoks and the overwintering period was lengthened; resembling field records more closely and indicating a fully tillered cover crop before occurrence of the first frost events. The end of the dormancy period was delayed to early March in the calibrated model, amounting to an 8-week difference relative to the uncalibrated model (~January). Predicted and observed Zadoks also correlated well following cover crop dormancy, with the calibrated model predicting rye stages between 30 and 40 Zadoks before cover termination in both years (i.e. jointing to booting stage). Literature reports for rye development in process-based models is currently limited. Errors for predicting wheat vegetative stages until jointing (Zadoks 30) have been shown to increase, especially in site simulations where phyllochron rates depart from conventionally accepted “100 phyllochron” rules (Wilhelm, McMaster, Rickman, & Klepper., 1993).

The phenological observations reported here, i.e. seedling to booting, or Zadoks 10 to 40, reflect the expected weather patterns for central Iowa and agree with reports for fall-seeded small grains across different environments, such as Northern Texas (35°N), Colorado (40°N) (McMaster, Klepper, & Wilhelm, 1991), or Alberta, Canada (52°N) (Baron, Dick, Salmon, & Mcleod, 1993). Development patterns are usually reported to change under strong environmental influence, e.g. soil moisture, soil nutrient status, or daylength, but except for planting date, phenology is rarely disrupted by specific management practices (Cao & Moss, 1991; Oakes et al., 2016). Thus, presumed delayed phenology due to limiting factors inherent to broadcast-seeding, such as unequal plant distribution, reduced plant

populations, or a shallow seeding depth, was not supported in this study and would likely have only limited impact on the prediction routines of a process-based model.

Biomass predictions between late November and early May were 130 and 2350 kg. ha⁻¹ for the 2015/2016 growing season, and 127 and 2707 kg. ha⁻¹ for 2016/2017 (RMSE= 860 kg. ha⁻¹, RRMSE= 0.56, figure 6). Biomass was predicted more accurately 1-week before termination, as in mid-April of both years, with predicted and observed biomass being close to 2000 kg. ha⁻¹. Biomass estimations agree well with field and research reports from this area. Winter rye has been extensively studied for its winterhardiness and potential to improve soil and water quality (Kaspar, Jaynes, Parkin, & Moorman, 2007; Kladvik et al., 2014; Strock, Porter, & Russelle, 2004), but has also been shown to display reduced biomass due to the limited window between seeding and first frost events. Rye biomass production within the 300-3000 kg. ha⁻¹ range reported here does reflect such weather constraints, but may also be the result of post-wintering reduced survival rates and tillering capacity (table 1), as well as the short time available for growth that exists between dormancy break and cover crop termination. Kaspar and Bakker (2015) hypothesized poor winter survival and reduced stands as the most influential factors limiting growth among certain rye cultivars in a multi-year evaluation of small grains adapted to central Iowa.

On the other hand, biomass overprediction was affected by the poor agreement between measured and predicted phenology of the cover crop. Feyereisen, et.al (2006) reported 70% agreement between observed and predicted cover crop biomass after calibrating a rye sub-module embedded into a water quality model in Minnesota. Additional studies relying on biophysical models, ranging in purpose and scale, have also reported predictions that fit biomass records in the US Upper Midwest , and imply the potential of

well calibrated models to estimate cover crop effects at larger scales, such as: estimating relative soil nitrate changes from tile drained fields (Malone et al., 2014), calculating expectations for additional rye biomass in maize and soybean rotations (Baker and Griffis, 2009), or exploring abiotic effects of rye shoot biomass on maize system performance (Martinez-Feria, Dietzel, Liebman, Helmers, & Archontoulis, 2016).

Testing of the calibrated rye model. APSIM was able to simulate biomass of broadcast-seeded rye satisfactorily when comparing field records from seven years in central Iowa (figure 8). Most importantly, root mean square error diminished considerably ($RMSE = 552 \text{ kg. ha}^{-1}$) whereas relative root mean square error remained close to the values during the calibration phase ($RRMSE = 0.58$). The validation dataset included a single biomass observation recorded in the fall and spring of consecutive years (November-May), but actual sampling dates were slightly different from those in the calibration set. Overall, biomass agreement was improved at low and mid ranges ($< 2000 \text{ kg. ha}^{-1}$), particularly by the end of fall, and years where spring biomass remained within that range. Still, poor lack of agreement at the end of the season may have been affected by uncertainty in planting date and seeding populations: two key central drivers of cover crop biomass not fully explored in our analysis. By calibrating influential parameters related to plant phenology and biomass, we showed consistent reductions in error sources affecting state variables germane to resource interception (i.e. LAI and dry matter initiation and expansion), yet final canopy size is also determined by plant stand and tillering dynamics in APSIM (Zheng et al., 2014). Because actual seeding rates employed in the field were not fully available, our model assumption of $140 \text{ plants.m}^{-2}$ based on field observations of a single season may not be fully representative of every year in the validation set. Running the model by delaying planting

dates, on the other hand, pushed spring biomass predictions and reduced prediction errors even further, albeit somehow artificially (data not shown).

Conclusion

Accurate representation of growth and development patterns are needed for assessing cover crop effects at the field-scale level. Phyllochron rates estimated at three thermal scales evidenced distinctive development patterns for the late-fall and early-spring periods following seeding of a rye cover crop. Phyllochron estimation was, however, sensitive to changes in the optimal ranges considered for calculation of thermal units (i.e. base temperatures at 0 and 4 °C), capturing responses in simple models adapted to temperate regions and showing more effective characterization of environmental responses than a mechanistic yet computationally intensive algorithm. APSIM and similar models that construct phenological rules via interpolation of effective thermal time (GDD) across critical ranges (cardinal temperatures) can bring more active contribution of the different inter-seasonal phyllochron responses into their algorithms for future versions. Also, by identifying and calibrating relevant parameters in a cover crop module embedded within APSIM, we detected high sensitivity in phenology and biomass predictions to: a) cultivar specific parameters delimiting thermal thresholds for stage transitioning (e.g. thermal accumulation from sowing to end of vegetative), and b) soil parameters controlling top soil water retention (e.g. minimum water content for germination). We recommend APSIM users to direct their calibration efforts towards these parameters for a correct representation of rye or similar species when simulating cereal cover crops and their contribution to maize and soybean cropping systems.

Figures and Tables

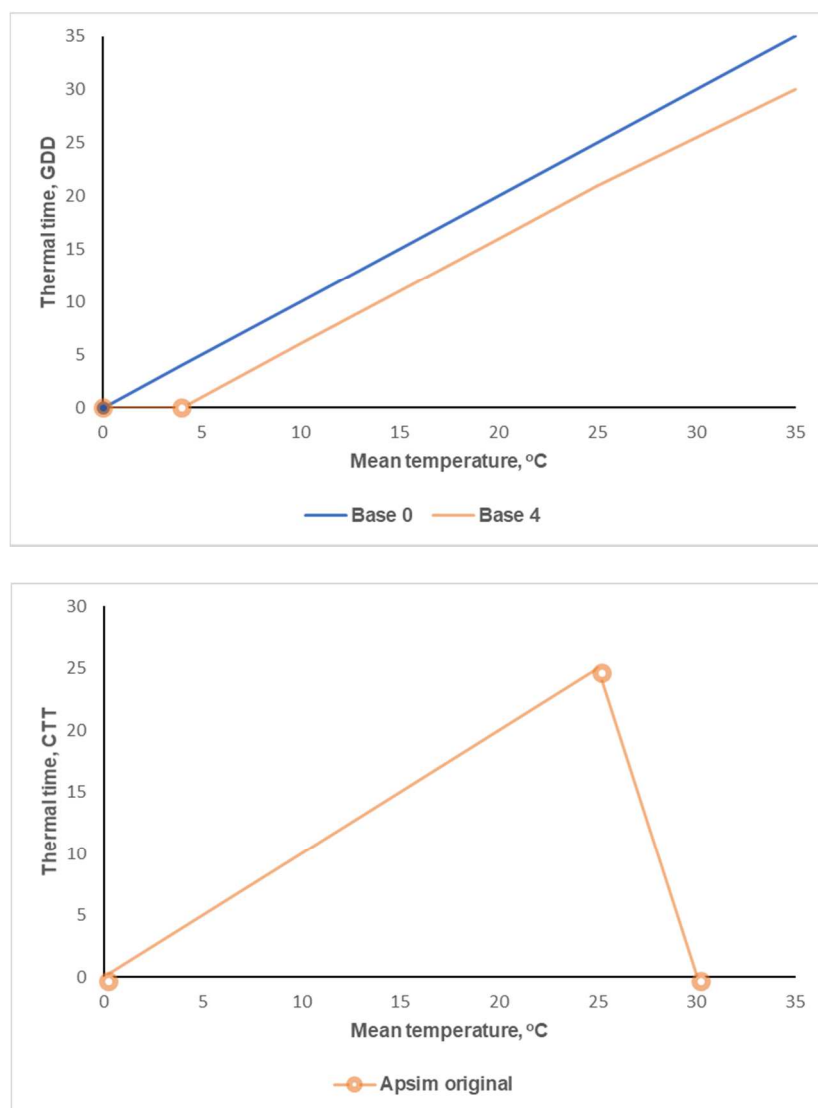


Figure 1. Thermal time calculation from three methods based on cardinal temperatures. Base 0 and Base 4 refer to minimum temperatures above which thermal accumulation begins. The Apsim method limits thermal time further by an optimal and a maximum values, and accounts for photoperiodic and vernalization effects.

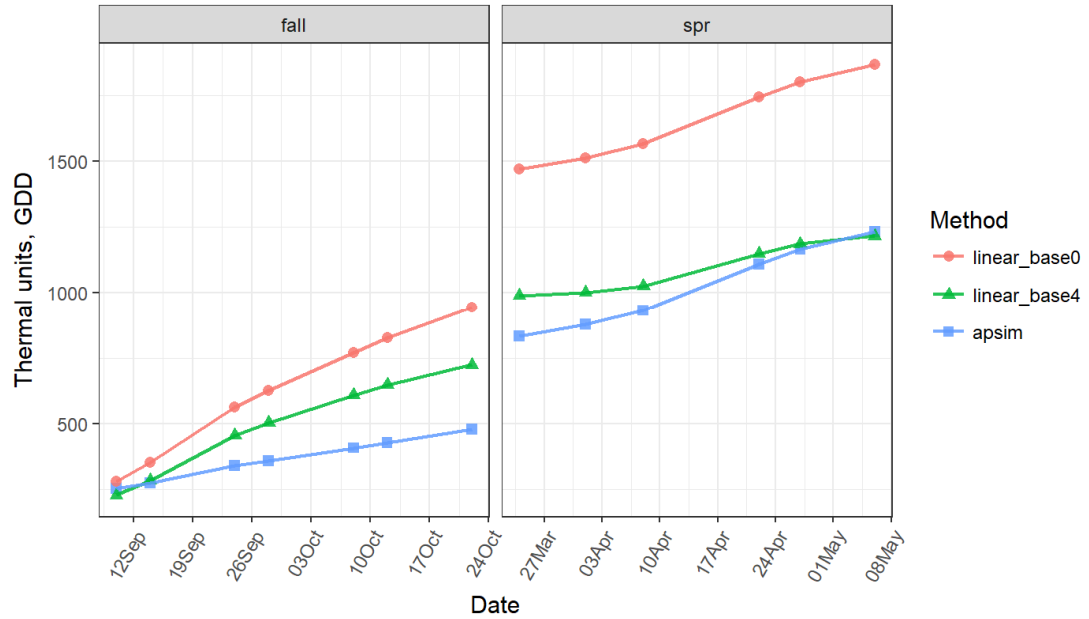


Figure 2. Thermal time accumulation for fall-seeded and spring-terminated winter rye in central Iowa (Sep/2016-May/2017). Linear base 0 and base 4 are minimum temperatures for cumulative thermal time. The “apsim” method is the crown based thermal algorithm in the APSIM-wheat model, and limits thermal time further by additional optimal and maximum values, and also accounts for photoperiod and vernalization effects.

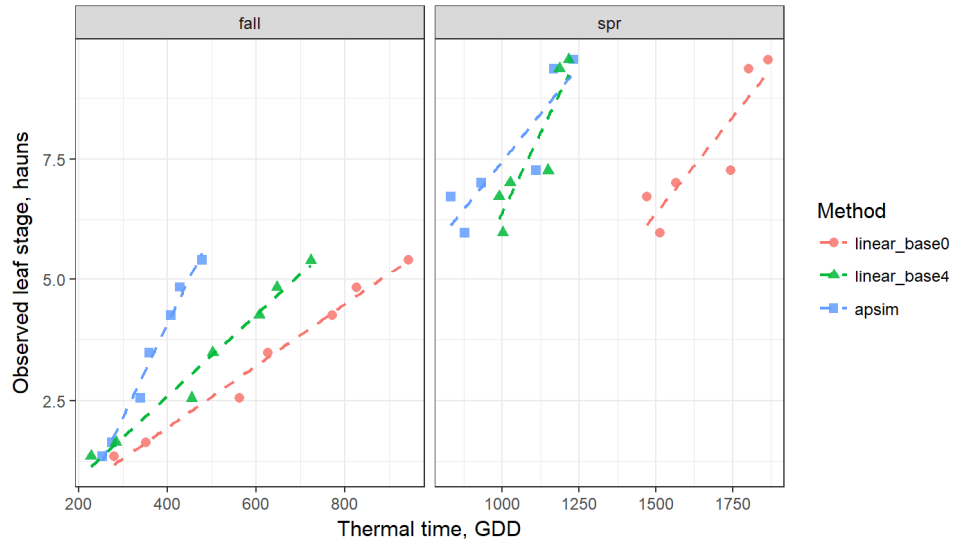


Figure 3. Rye leaf stages as a function of thermal time after seeding. Thermal time calculated from three methods. Linear base 0 and base 4 are minimum temperatures for cumulative thermal time (GDD). The “apsim” method is the crown based thermal algorithm in the APSIM-wheat model, and limits thermal time ($CTT \approx \text{physiological days}$) through additional optimal and maximum temperatures, and also accounts for photoperiod and vernalization effects. Reciprocals from the regression slopes in each panel represent seasonal phyllochron rates [$\text{GDD} \cdot \text{leaf}^{-1}$ for base 0 and base 4, or $\text{CTT} \cdot \text{leaf}^{-1}$ for apsim] calculated in table 4.

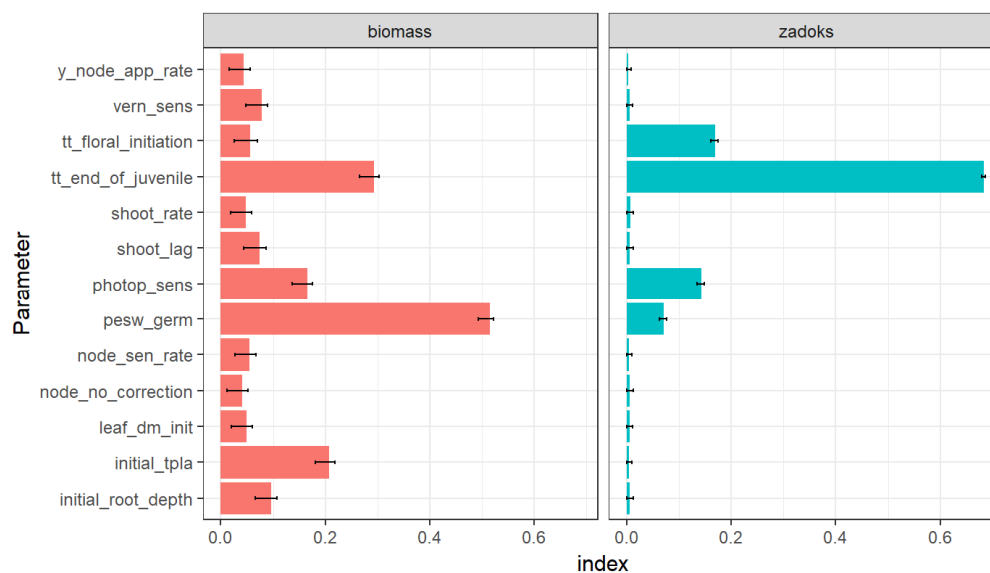


Figure 4. Sensitivity rankings for influential parameters in simulated phenology (Zadoks) and biomass of fall-seeded and spring-terminated winter rye in central Iowa. Horizontal lines at the top of the bars are 95% bootstrap replicates. Index (0-1) indicates the % in model output variability caused by parameter variation ($\pm 50\%$ around default).

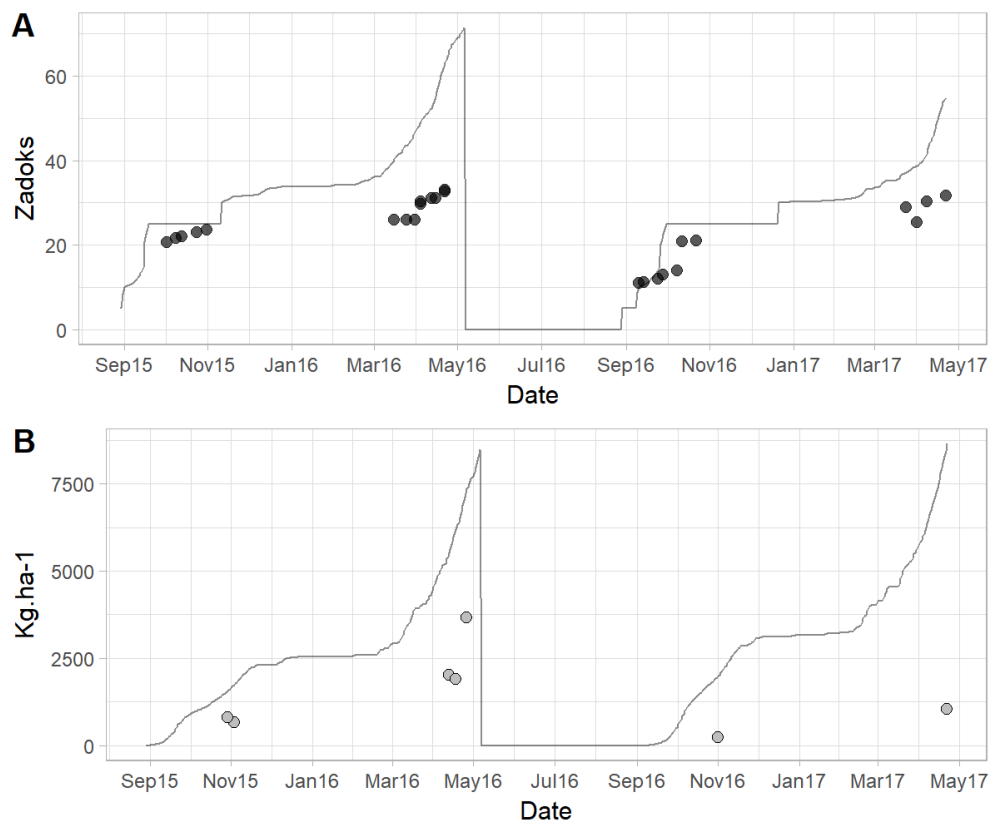


Figure 5. Pre-calibration runs of simulated phenology (A) and biomass (B) of a fall-seeded and spring-terminated rye cover crop in central Iowa (2015/2016-2016/2017).

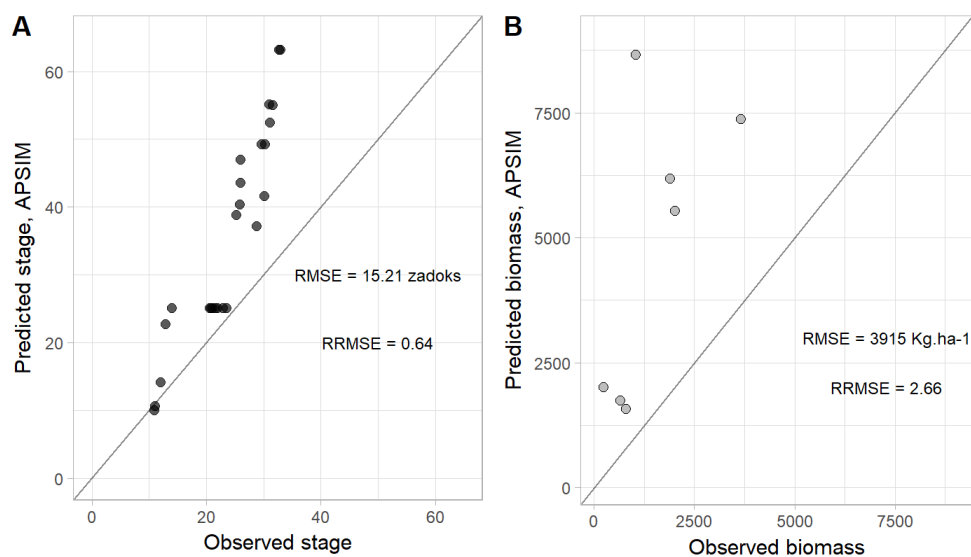


Figure 6. Agreement between predicted and observed phenology and biomass of rye cover crop in Iowa (pre-calibration). Zadok observations are averages for 10 randomly selected plants, sampled weekly at two locations. Biomass observations are means for 8-12 replicates sampled in late-fall (November/2016) and 7-days before termination (April/2017).

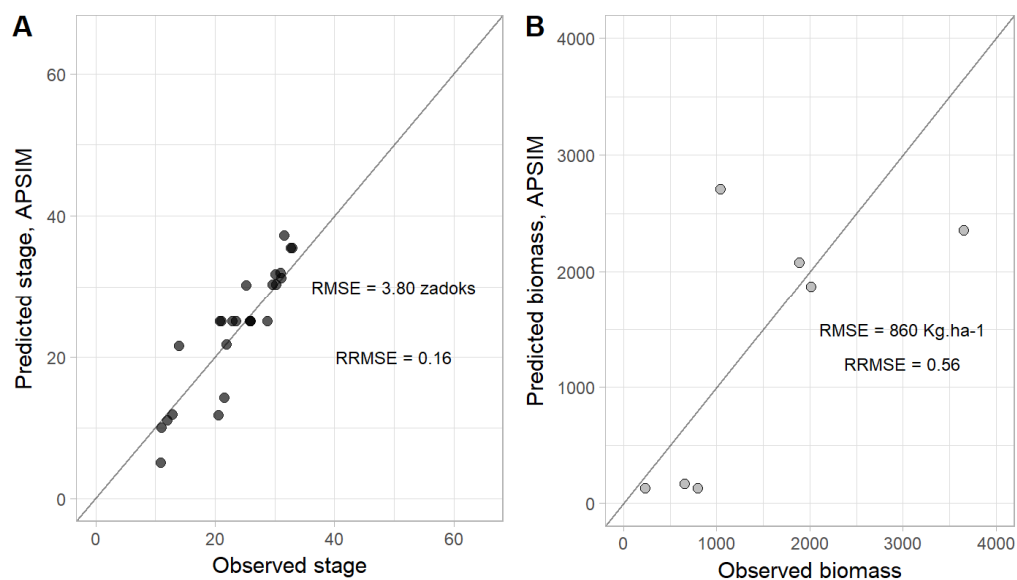


Figure 7. Agreement between predicted and observed phenology and biomass of rye cover crop in Iowa (post-calibration). Zadok observations are averages for 10 randomly selected plants, sampled weekly at two locations. Biomass observations are means for 8-12 plots sampled in late-fall (November/2016) and 7-days before termination (April/2017).

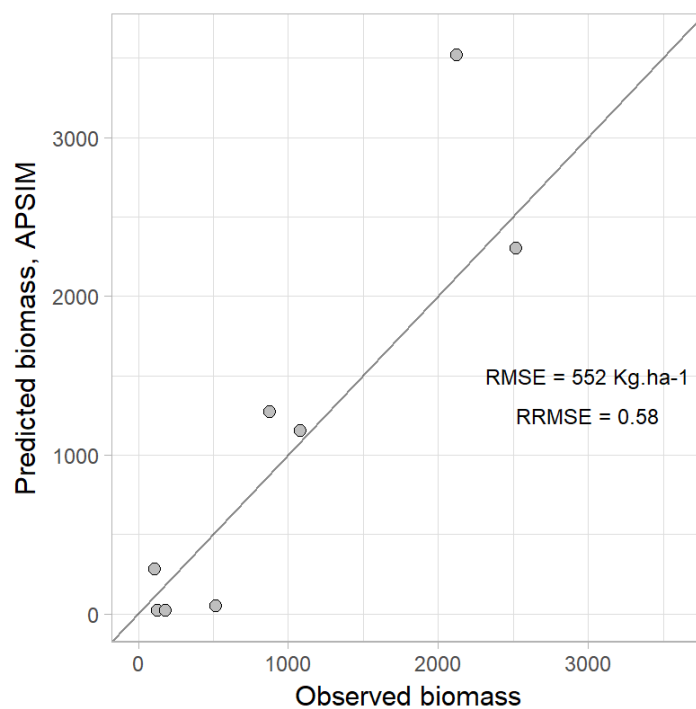


Figure 8. Model testing of rye biomass in Iowa (2012-2015). Biomass observations are means of 8-12 rye plots sampled in late Fall (November) and late spring (April) of consecutive years. Biomass pairs are for fall-seeded rye that was terminated the subsequent spring (e.g. fall 2012-spring 2012, fall 2012-spring 2013). Data was available for 4 cover crop years.

Table 1. Parameters in the winter wheat module selected for sensitivity analysis

| APSIM identifier | Units | Default value | Process | Description |
|----------------------|---------------------------------------|---------------|------------------|---|
| leaf_dm_init | g plant ⁻¹ | 0.003 | Biomass | Initialization of leaf dry matter |
| y_node_app_rate | °C day ⁻¹ | 95 | Leaf development | Thermal time for node appearance |
| initial_tpla | mm ² plant ⁻¹ | 200 | Leaf area | Initialization of leaf area expansion |
| node_sens_rate | °C day ⁻¹ | 60 | Senescence | Senescence node rate |
| shoot_lag | °C day ⁻¹ | 40 | Emergence | Thermal time before root growth |
| shoot_rate | °C day ⁻¹ mm ⁻¹ | 1.5 | Emergence | Thermal time for root elongation |
| pesw_germ | mm ⁻¹ mm ⁻¹ | 0 | Germination | Available water limiting germination |
| initial_root_depth | mm | 100 | Root elongation | Initial root extension |
| tt_end_of_juvenile | °C day ⁻¹ | 400 | Phenology | Thermal time between emergence and end of juvenile stages |
| tt_floral_initiation | °C day ⁻¹ | 555 | Phenology | Thermal time between end of juvenile and floral initiation stages |
| photop_sens | --- | 3.0 | Phenology | Sensitivity to photoperiod affecting thermal time |
| vern_sens | --- | 1.5 | Phenology | Sensitivity to vernalization affecting thermal time |

Table 2. Weather events and field operations for two cover crop seasons at two sites in central Iowa. Parentheses are 30-year averages.

| | Date | | Total Rainfall (mm) | |
|-------------------|-----------|-----------|---------------------|-----------|
| | Kelly | Isuag | Kelly | Isuag |
| Cover planting | 3-Sep-15 | 10-Sep-15 | 0 (1) | 0 (2) |
| Grain harvest | 6-Oct-15 | 2-Nov-15 | 119 (88) | 105 (116) |
| First frost | 21-Nov-15 | 21-Nov-15 | 218 (174) | 166 (151) |
| Last frost | 20-Mar-16 | 20-Mar-16 | 488 (324) | 436 (301) |
| Cover termination | 25-Apr-16 | 25-Apr-16 | 564 (425) | 512 (402) |
| Cover planting | 29-Aug-16 | 26-Aug-16 | 2 (5) | 0 (5) |
| Grain harvest | 20-Oct-16 | 1-Nov-16 | 199 (127) | 203 (165) |
| First frost | 7-Dec-16 | 7-Dec-16 | 264 (212) | 265 (225) |
| Last frost | 16-Mar-17 | 16-Mar-17 | 393 (332) | 393 (346) |
| Cover termination | 22-Apr-17 | 27-Apr-17 | 520 (430) | 520 (464) |

Table 3. Establishment of a broadcast-seeded rye cover crop at two sites in central Iowa. Means and 95% confidence intervals are included in parenthesis.

| | | Plant counts, plants.m ⁻² | | Ground cover, % | |
|--------|-------|--------------------------------------|----------------|-----------------|-------------|
| | | Fall 2015 | Spring 2016 | Fall 2015 | Spring 2016 |
| Year 1 | Kelly | 228 (180, 274) | 184 (160, 207) | 5 (3, 9) | 32 (25, 41) |
| | Isuag | 258 (206, 309) | 115 (85, 144) | 2 (1, 4) | 26 (20, 37) |
| | | Fall 2016 | Spring 2017 | Fall 2016 | Spring 2017 |
| Year 2 | Kelly | 255 (209, 302) | 153 (129, 176) | 5 (3, 9) | 34 (26, 43) |
| | Isuag | 306 (254, 358) | 136 (106, 165) | 2 (1, 3) | 56 (54, 69) |

Table 4. Rye leaf stage vs. thermal time (GDD, CTT). (p) is the probability that the slope difference between fall and spring is equal to zero, i.e. $\Delta \beta = 0$.

| Thermal time method | | GDD x Season | | |
|--|---------------------------|---------------|---------------|-------------------------|
| | | Fall | Spring | $ \Delta \beta $ (p) |
| CMA | Slope (β) | 0.0192 | 0.0079 | 0.0113 (0.003) |
| (APSIM crown model) | | | | |
| (CTT.leaf ⁻¹ \approx Physiological days) | Phyllochron (1/ β) | 52.08 | 126.50 | |
| 4B | Slope (β) | 0.0084 | 0.0126 | 0.0042 (0.013) |
| (Linear base 4) | | | | |
| (GDD.leaf ⁻¹) | Phyllochron (1/ β) | 119.04 | 79.35 | |
| 0B | Slope (β) | 0.0063 | 0.0079 | 0.0016 (0.031) |
| (Linear base 0) | | | | |
| (GDD.leaf ⁻¹) | Phyllochron (1/ β) | 158.73 | 126.58 | |

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CHAPTER 5. CONCLUSIONS

The goal of this research was to advance the scientific understanding of maize productivity impacts given by changes in cover crop decision making and use this knowledge to target practices that reduce soil and water quality deterioration without penalizing yields and farm returns.

Maize rotations that included one or more cover crop in association displayed yields consistently higher than those that did not. Grass cover crops neither increased nor decreased maize yields whereas legumes or mixtures increased yields at different levels of a no cover crop control. Legumes contributed to higher yields mainly through higher N mineralization rates, expressed more fully in low-fertilized environments and no-tilled soils. Mixtures respond positively to late termination periods by accumulating biomass that control summer weeds and conserve water in dry regions. In retrospective, significant yield differences were mostly noted during early research periods in warmer areas of the United States, from mid-1980s to early 1990s, where establishment is favored by longer growing seasons.

Maize growers planting a winter cover crop can benefit from long and short-term contributions to their operations. Soil and water benefits are not directly monetized but build up over time and depend on successful establishment of the cover crop. Rye biomass was shown to significantly reduce erosion, runoff, and N-leaching across different regions or soil-drainage conditions in Iowa, but showed also little incentives for farmers in weather-limited areas to increase cover crop populations. Although seeding costs are significant, maize growers who also graze cover crops are more likely to reduce the expectations of diminishing farm returns. Growers receiving cost-sharing assistance may benefit from late grazing

periods where more biomass is produced and higher savings would result by saving more on forage or hay supplementation.

Enhancing rye representation in APSIM contributed to more effective biomass predictions at the field-scale level. Development patterns of winter rye were shown to differ between the periods of active cover crop growth, i.e. late-fall and early-spring, although the magnitude of such effects was highly dependent on the thermal scale utilized. Process-based models that construct their phenological routines based on interpolation of critical ranges of temperature could bring a more active role of fall and spring phyllochron rates into their structures. A more effective characterization of leaf development translates into timely biomass partition and allocation, so tracking plant vegetative status becomes key if cover crops effects on a maize system are to be investigated with a simulation model. Furthermore, calibrating model parameters is time and resource consuming, but I was able to find major sources of variability in rye phenology and biomass predictions. Future APSIM users who want to simulate a cereal cover crop can optimize their calibration efforts by targeting a cultivar-specific parameter controlling thermal accumulation between sowing and end of the vegetative phase, and a soil parameter limiting water content for germination.

This research evidenced the potential of cover crops for improving maize productivity while minimizing the negative outcomes associated with it. By looking at cover crops at the country-level, I confirmed that cover crop benefits are not unique and change across regions and scales. Exploring the agronomic and economic relationships of rye biomass and plant populations, I found the incentives that grazing rye biomass may bring to maize growers who may be otherwise reluctant to use cover crops. Finally, by studying winter rye as an independent species, I explored physiological principles and mechanisms in which rye and

maize interact so that process-based models can be enhanced for future cover crop evaluation at larger scales.