# Unraveling the ecological yield gap in continuously grown maize

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# Abstract

Ecological processes provide significant contributions to agricultural productivity, but in many instances are not well quantified, and therefore may not be fully utilized or modelled. An apposite example is the continuous maize (*Zea mays*) penalty, wherein maize grown continuously on the same land generally requires more inputs to achieve equivalent yields and conjointly produces lower maximum yields compared to maize alternated with soybean (Glycine max). While this phenomenon is well-documented, a mechanistic understanding of the drivers has remained elusive. To aid in In the present study we sought to conceptually define agronomic and ecological yield gaps, estimate the gaps empirically, and to identify potential causal mechanisms and their physical expressions in cropping systems. To achieve these objectives, we used

(1) used 157 site-years of experimental data from the US Corn Belt to quantify how soil, weather, and their interaction drive variation in the continuous maize penalty, (2) synthesized results with existing literature and modelled scenarios to identify probable mechanistic pathways, (3) tested approaches for modelling the penalty, and (4) provided recommendations for future research. Experimental data consisted of nitrogen (N)-response curves for maize yields from continuous maize and maize-soybean (*Glycine max*) rotations in Iowa (7 sites) and Illinois (7 sites) conducted between 1999 and 2016. Maximum continuous-and rotated-maize yields averaged 8.7 and 9.7 Mg ha-1 over the study period, and both increased 213 (SE:36) kg ha-1 yr-1 from 1999-2016, rendering the continuous maize penalty steady over time at an estimated 1.0 (SE:0.2) Mg ha-1 (mean of 10% yield penalty). The penalty ranged from 0-4.8 Mg ha-1, and soil contributed to only 13% of the variation. The amount of rainfall during the two weeks prior to planting was positively associated with penalty sizes. Applying additional N above the optimal rate for rotated-maize eliminated the penalty in only 6 out of 157 site-years and was less effective in colder environments. Synthesizing these results with existing literature and a processed-based model (APSIM), we hypothesize compromised maize roots in maize monocultures is a significant driver of the penalty. To our knowledge, there is limited data to refute or support this hypothesis. We identify a suite of field measurements that would best identify the mechanistic underpinnings of the continuous maize penalty including growth analyses, residue amounts (total and surface), root front velocity, kernel number and size, maximum root length and biomass, and residual nitrogen at maturity. These measurements would support efforts to manage, breed for, and model the continuous maize penalty, representing a major step forward in maximizing the efficient use of arable lands.

# Introduction

Maize grown for two or more consecutive years comprises almost a third of the cropland area in the mid-western area of the United States (US) (Boryan et al., 2011; Tomer et al., 2017). However, even with high inputs, maize yields less when it is preceded by maize compared to another crop. This phenomenon has been observed globally in both high- and low-input cropping systems and is often referred to as the continuous maize yield penalty (Rao and Mathuva, 2000; Bennett et al., 2012; Vasileiadis et al., 2013; Beillouin et al., 2019). Numerous studies in the US Midwest have established that yields of maize grown in monoculture are lower than yields of maize rotated with soybean (*Glycine max*), (Dick and Doren, 1985; Peterson et al., 1990; Meese et al., 1991; Crookston et al., 1991; Porter et al., 1997; Varvel, 2000; Stanger and Lauer, 2008; Gentry et al., 2013; Al-Kaisi et al., 2015; Farmaha et al., 2016; Seifert et al., 2017; Vogel and Below, 2018; Bowles et al., 2020), but there has been less work exploring the mechanisms responsible for the penalty. While the penalty is consistent, it exhibits a large degree of variability. In the US, experimental studies report average penalties ranging from 5-30% (Erickson, 2008), but even at high nitrogen (N) rates the penalty at a single site can vary from 0-25% depending on the year (Porter et al., 1997). A report from 239 site-years across seven states showed only a modest increase in continuous maize yields (~3%) with stover harvest in only half of the site-years, demonstrating the penalty is not simply a function of total residue (Karlen et al., 2014) Similarly, a multi-site study found the continuous maize penalty was not affected by tillage intensity (Al-Kaisi et al., 2015; Fig. S1), indicating the penalty is not solely driven by surface residue effects. A series of studies done in Minnesota likewise rejected the hypothesis that residue is solely responsible for the yield penalty (Crookston and Kurle, 1989), and found evidence of more water uptake in rotated maize (Copeland et al., 1993), higher concentrations of N, phosphorous, and potassium in rotated maize leaf tissue (Copeland and Crookston, 1992), and possible links to differences in mycorrhizal populations affecting root characteristics (Johnson et al., 1991, 1992; Nickel et al., 1995). A study in Wisonsin found soil fumigation eliminated the continuous maize penalty in one year (Turco et al., 1990). However, results from a single site may not be transferable, as it is clear the penalty is the result of a complex interaction between soils, management, and weather (Dick and Doren, 1985; Porter et al., 1997; Gentry et al., 2013; Al-Kaisi et al., 2015). Studies based on surveys or satellite imagery provide larger inference scopes, but are associative and conclusions are often too broad for field-based inference (Farmaha et al., 2016; Seifert et al., 2017). Therefore, despite the penalty being well- documented, the driving causes have remained elusive, rendering the penalty difficult to predict and manage for. Data from long-term, replicated experiments at multiple sites can provide critical insight into complex cropping system questions (Poffenbarger et al., 2017; Bowles et al., 2020; Cusser et al., 2020), offering the advantages of controlled experiments with the scope of inference needed to extract generalizable patterns. Therefore, long-term multi-site datasets are best suited for answering questions about the continuous maize penalty.

Managing the penalty without knowledge of driving mechanisms is challenging. Currently, producers are advised to increase N applications to maize following maize by ~60 kg ha-1 compared to maize following soybean (Sawyer et al., 2006). While this is effective on average, it is unclear how the effectiveness varies by year and soil, as in many instances the additional N application may not translate to increased yields in the continuous maize system. Over-application of N above the agronomically optimum nitrogen rate (AONR) in continuous maize systems carries significantly more risk of nitrate leaching compared to rotated maize systems (Pasley et al., 2021), decreases root mass (Ordóñez et al., 2021), and over time depletes soil carbon stores (Poffenbarger et al., 2017). Furthermore, the additional N application recommended for maize monocultures results in increased emissions of nitrous oxide, a potent greenhouse gas (Millar et al., 2010; Grace et al., 2011). Given the prevalence of continuous maize in the Midwest, predicting when N application will translate to increased yields is therefore vital for protecting water quality, maintaining soil productivity, and reducing climatic impacts of agriculture. Moreover, applying N without an accompanying increase in yields reduces producer profits.

In addition to helping producers optimize their cropping systems, a mechanistic understanding of the continuous maize penalty will also allow researchers to incorporate the penalty into processed based models to better capture land-use decisions and the environmental impacts of cropping system choices. Many bio-physical process-based models are available for simulating agricultural systems (Jones et al., 2017; Boote, 2019; Silva and Giller, 2021), but to our knowledge none directly incorporate the continuous maize penalty that is caused by non-water and non-N factors, resulting in a consistent over-prediction of continuous maize yields, regardless of the model (Figure 1).

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Figure 1 Summary of 157 site-years of experimental data compared to uncalibrated APSIM model predictions show good agreement with maize-soybean system maize yields, but a consistent over-estimation of continuously grown maize yields

Through calibration, Puntel and collegues (Puntel et al., 2016) were able to simulate a quarter of the observed penalty using the Agricultural Production Systems sIMulator (APSIM) model (Keating et al., 2003; Holzworth et al., 2014), indicating a substantial portion of the penalty requires additional model capabilities.

The majority of cropping system models focus on simulating abiotic processes to predict attainable yields (Silva and Giller, 2021), with the assumption that disease and pests are adequately controlled. In any given year, the continuous maize penalty is likely a function of both biotic and abiotic conditions. Direct modelling of biotic components would require a substantial increase in the complexity of processed-based models. Pests not only depend on local conditions (soil moisture, air temperature, humidity), but also on complex regional interactions including physical, biological, social, and economic factors (Esker et al., 2012). Incorporating these factors into a single model is not trivial, and would require coordinated efforts to improve data collection and reporting (Donatelli et al., 2017). However, while modelling the biotic factors directly may not be desirable or feasible, incorporating the physical manifestations of biotic effects may be sufficient for certain purposes. Understanding the simplest avenues for incorporating the continuous maize penalty into process-based models would be universally advantageous for researchers working with maize-based systems.

The goal of this study was to use multi-site, multi-year data coupled with an in-depth literature review and a process-based model (APSIM) to gain insight into factors contributing to the continuous maize penalty and how best to model those effects. Specifically, our objectives were to:

(1) Use experimental data to quantify site and environmental variation in the continuous maize penalty

(2) Synthesize results with existing literature and modelled scenarios to identify probable mechanistic pathways

(3) Use a calibrated model to test hypotheses and approaches for modelling the penalty

(4) Provide recommendations for future research

# Methods and Materials

We used a combination of literature review and experimental observations taken in a field setting to inform model building and testing (Figure 1).A screenshot of a computer

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Figure 2 Schematic of approach

## Experimental data

Site-year averaged yield data from long-term N-rate trials conducted at seven sites in Iowa and seven sites in Illinois were used for this study (see **Figure 6)**. Details about site management are available in supplementary material (**Table S1**). Briefly, treatments consisted of cropping system (continuous maize, maize-soybean rotation with both phases present every year) and maize nitrogen (N) fertilization rate (S0-270 kg ha-1. Each site had three or four replications of each treatment arranged in a randomized complete block design. Weeds were adequately controlled using herbicides and fungicides were used on an as-needed basis. All nutrients other than N were managed for optimum maize production (soil pH, P, and K levels were tested; lime and fertilizer were applied if needed). Nitrogen fertilizer was applied near planting (± 10–15 days), and in some cases as side-dressing. Three sites in Illinois were managed using no-till practices, while the remaining sites were chisel plowed in the fall with spring field cultivation.

## Statistical analyses

All statistical analyses were done using R version 4.0.3 ((R Core Team,)and using the *tidyverse* collection of packages (Wickham et al., 2019). Mixed-effect linear models were fit using the *lme4* package (Bates et al., 2015) with means estimated using the *emmeans* package (Lenth et al., 2018), and non-linear models were fit using the *nlraa* package (Miguez, 2021a). Assumptions of normally distributed errors and equal variance were explored, and Akaike’s Information Criteria (AIC; Bozdogan, 1987) were used to identify the best models when appropriate.

### Quadratic plateau models

To estimate the maximum yields for each site-year’s cropping system (rotated, continuous) a quadratic plateau was fit to each site-year for each system’s maize yields as a function of N fertilization rate (e.g. Figure 2). We chose to use a quadratic plateau because it is a commonly used model for yield-N response curves (Cerrato and Blackmer, 1990) and it converged for the majority of site-years of our data. The agronomically-optimum-nitrogen-rate (AONR) is the N-rate at which grain yield ceases to statistically increase with additional N application, and is estimated using parameters fit from the quadratic plateau model. The difference between the two system’s yields at the rotated-AONR is hereafter referred to as the full penalty. Using the quadratic plateau method, we separated the full penalty into two components: the observed penalty, and the N-compensatable penalty. The observed penalty is the difference between the two system’s maximum yields. The N-compensatable penalty is the amount of yield that was gained in the maize monoculture by applying N fertilizer in excess of the rotated-AONR. The N-compensatable penalty was estimated as the difference between the maize monoculture yield at the rotated-AONR and the maximum maize monoculture yield. There is a large amount of uncertainty in AONR estimations from one site-year of data, and we recognize the estimation of the N-compensatable penalty propagates that uncertainty. We therefore do not interpret the N-compensatable penalty as a robust estimation but rather use it only as an indication of whether the N-compensatable and observed penalty are related. The correlation between the two components was assessed using a non-parametric Spearman correlation (Zar, 1972).

If quadratic plateau models did not converge for one or more of the cropping systems in a given site-year, the site-year’s full penalty and its components were labelled as in-estimable. All fits and component estimates will be available as a csv upon acceptance of publication. For simplification, the yields at each system’s respective AONR rates are hereafter referred to as maximum yields.

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**Figure 3** Conceptual diagram of parsing the full penalty into the amount of penalty that is compensated for through additional nitrogen (N) fertilization (yellow box) and the remaining continuous maize penalty that is observed even at high N inputs (green box). Data is from IA-4 2003, original data (circles) are connected by a dotted line to aid in viewing with quadratic plateau model predictions (thick lines) and estimated agronomically-optimum-nitrogen-rate (AONR) for each system (large diamonds).

### Mixed effect linear models

The percentage of the full penalty that was compensated for through additional N fertilization over the rotated-AONR was calculated for each site-year. The conditional value for each site was estimated using a mixed-effects linear model with the percentage as the response variable, site and a year-factor as random intercepts.

Changes in maximum maize yields and the observed penalty over time were assessed using a mixed-effect linear model. For the maximum yield analysis, maximum yields were the response variable with a fixed effect of cropping system (rotated, continuous), year as a continuous variable, their interaction, a random slope for each site-year, and a random intercept for site. Additionally, the relationship within a site was investigated to ensure the overall effect was not masking different within-site patterns; this was done using a site-by-year interaction. The significance of the change in penalty over time was estimated by subtracting the maximum continuous maize yields from the maximum rotated maize yields at each site-year and fitting a mixed-effect linear model with the penalty as the response variable, year as a fixed effect, and a random slope for each site-year and a random intercept for site.

Overall maximum yields of each system were compared using a mixed-effect model with the max-yield as the response variable, cropping system as a fixed effect, and a random intercept for both site and a year-factor. We included a year-factor because it significantly improved the model fit, and exploratory analysis indicated that the air temperatures of each site were clustered by year. For example, 2012 was a warm year at every site (supplementary material). The mean continuous penalty was estimated using a mixed-effects model with site and a year factor as random intercepts. The contributions of site and year-factor to variation in the observed continuous maize penalty were assessed using the *rptR* package (Stoffel et al., 2017).

### Feature selection models

To identify soil, weather, and management associations with the continuous maize penalty, we assembled a dataset with various metrics important to maize production in the Midwest (**Table S2**). We performed both a principal component analysis (PCA) and calculated a correlation matrix to inform the creation of a set of independent predictors (Chandrashekar and Sahin, 2014). The resulting predictor set was used in both step-wise model selection using Bayesian Information Criteria (Venables and Ripley, 2013) with the base R function *step*, and in a partial least squares regression (PLS) with the *pls* package (Bjørn-Helge et al., 2020) to identify predictors associated with the observed penalties. The number of included components in the PLS regression (two components) was determined based on visual inspection of the root-mean-squared-error. The importance of each predictor was estimated using the *varImp* function of the *caret* package (Kuhn, 2018), which uses the sums of the absolute regression coefficients weighted proportionally to the reduction in the sums of squares. The robustness of the results was assessed by running each model on a predictor set where one predictor was removed and comparing the results from the full predictor set.

## APSIM Modelling

All modelling activities were informed by the literature review and experimental data (Figure 2). Modelling was done using APSIM v.9 with the SWIM module (Huth et al., 2012)and custom scripts to simulate water table dynamics (Ebrahimi-Mollabashi et al., 2019; Archontoulis et al., 2020). APSIM has been shown to adequately simulate N- and water-dynamics in Midwestern maize-based systems (Archontoulis et al., 2014; Dietzel et al., 2016; Puntel et al., 2016; Martinez-Feria et al., 2019; Pasley et al., 2021) and is appropriately structured for simulating multi-year effects of cropping systems (Basso et al., 2019). Soil profiles for the model were built using SSURGO data (Soil Survey et al., 2018) and adjusted using on-site measurements along with estimates from the USDA’s web soil survey tool. All management activities were taken from field logs. Weather data was taken from on-site weather stations through the Iowa Mesonet for Iowa sites (Iowa Environmental Mesonet) and XX for the Illinois sites (CITE). The maize and soybean phases were simulated using the APSIM maize 7.9, and individual cultivars were built to reflect maturity groups of each variety used. Surface organic matter and soil N and C cycling were simulated with the soil and surface models in 7.9. Soil temperature simulated with the optional physics-based model (Campbell, 1985) as this found to provide superior estimates to the default module (Archontoulis et al., 2014). For each site, simulations were run using a 5 year spin-up of a generic maize and soybean rotation with 170 kg N ha-1 of fertilization, followed by experiment-specific management and weather. All models were run sequentially without a yearly soil reset to best represent cropping system legacy effects.

### Scenario testing

To explore the role of water dynamics in the continuous maize penalty, we used calibrated models (Baum, unpublished data) and artificially lowered the radiation-use-efficiency of the maize cultivars in the continuous maize system to achieve an average of 10% lower grain yields. We then compared the soil water contents at several depths across the season in the rotated- and continuous-maize models over 17 years at four sites using a generalized additive mixed effect model with 35 knots, a fixed effect of rotation, and a random effect of a year-factor fit to each site individually using the *mgcv* package in R (Wood, 2011).

To explore the potential for changes in model parameters to capture the continuous maize penalty, the APSIM model was calibrated to the maize-soybean rotation subset of the yield-response-to-N experimental dataset using site-specific cultivar and soil parameters. The model predicted maize and soybean yields in the maize-soybean rotation with an R2 of x and x, and RMSE of X and x, respectively (**Figure S4**). The calibrated maize-soybean rotation model at a given site’s highest N rate (253 or 270 kg N ha-1) was used for scenario testing.

Using the above model as a baseline, management was changed to reflect the continuous maize systems per site-year. Select parameters in the continuous maize model were then adjusted one-at-a-time using the *apsimx* package (Miguez, 2021b) in R, and the model was re-run using the adjusted parameter value. The scenario’s penalty was calculated as the difference between the calibrated model’s predicted yields for the rotated maize model in a given site-year, and the given scenario model’s predicted yields for the continuous maize model in that same site-year.

### Dynamic scripts

To explore the possibility of having model parameters change dynamically in response to specified conditions, we built two generalized APSIM scripts. One script kills plants as a function of the running-average of soil temperature and/or moisture at user-specified depths. The other allows the user to assign a penalty to a crop parameter of their choice as a function of running averages of soil moisture, soil temperature, and/or the amount of surface residue at planting. More details are available in supplementary material.

# Results and Discussion

## Experimental data

Over the duration of the experiments (1999-2016), maximum maize yields increased significantly at a rate of 0.21 Mg ha-1 (SE:0.04), regardless of cropping system (**Figure 2**). The continuous maize penalty remained steady at 1.02 Mg ha-1 (SE:0.15), or approximately 10% of the rotated maize yields.

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**Figure 4** Maximum grain yields for maize grown continuously (pink triangles), in rotation with soybean (blue circles), and the difference between the two (continuous maize penalty, green squares) from 1999-2016.

The continuous maize yields were a significant predictor (p<0.001) of the penalty, while rotated maize yields were not (p=0.18), meaning variation in the penalty is better explained by the monoculture’s yields.

Results from the quadratic plateau estimations of the N-compensatable penalty and observed penalty show N fertilization eliminated the continuous maize penalty in only 6 of the 157 sites years. On average the N-compensatable penalty was smaller than the observed penalty, averaging 0.43 Mg ha-1 compared to 0.93 Mg ha-1, respectively (**Figure** 4). The N-compensatable penalty varied from 0-100% of the full penalty, but in the majority (70%) of site-years it represented less than half of the full penalty. On average, N-fertilization compensated for only 39% of the full penalty (**Figure** 4).

Diagram

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**Figure 5** (*Left*) Pyramid plot of each penalty type by site-year ordered by observed yield penalty; undetermined means quadratic plateau models failed to converge for one or more cropping system (*Right*) Frequency distributions of the size of the nitrogen-compensatable (yellow) and observed yield penalties (green).

There was no correlation between the size of the N-compensatable and observed yield penalty (**Figure S2**). Of the 121 site-years with estimable penalties, two-fifths (49) had observed penalties that were 10% or less of the rotated maize yields, while the remaining three-fifths (72) had penalties 10-50% of the rotated-maize yields (**Figure** **6**). The highest observed penalty was 4.79 dry Mg ha-1, observed at site IL-2 in 2003, corresponding to a 49% reduction in yield compared to the rotated maize yield. Site (e.g. soil) accounted for 13% of the variation in the observed penalty. The year-factor accounted for an additional 14%, with the soil-by-year interaction contributing the remaining 73%.

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**Figure** **6** (*Top left*) Map of site locations, (*top right*) histogram of frequency of penalty size as a percentage of the rotated-maize yield, and (*bottom*) boxplots of the observed continuous maize penalty ordered by site mean (italic values, n is number of site-years with estimable penalties) and shaded by latitude.

Not every site had trials in each year, but 2012 had the highest mean penalty (n = 5; 2.0 Mg ha-1) and 2016 the lowest (n = 5; 0.3 Mg ha-1; **Figure S3**). In general, Iowa sites had higher penalties than Illinois.

Weather factors were more consistently identified as important compared to soil factors in the predictor-selection models (step-wise, PLS). Both consistently identified the amount of precipitation two weeks before planting and the number of days below -15 deg C between 1-Jan and planting as important model features. PLS importance scores were highest for the pre-plant precipitation, followed by winter cold days, with both being consistently identified in the leave-one-predictor-out sensitivity analysis. The step-wise regression estimated the penalty increased 37 kg ha-1 (SE: 9.6) for each additional cold day, and increased 9.9 kg ha-1 (SE: 3.0) for each additional mm of precipitation in the two weeks before planting. No soil characteristics were consistently identified as important features, suggesting the higher penalties in Iowa compared to Illinois may be more related to weather and/or management differences rather than soil characteristics.

## Mechanistic pathways

### Literature

Literature reports mixed results with regards to the time component of the continuous maize penalty. Studies that utilize staggered start dates for assessing the years-in-maize effect, and therefore de-confound years-in-maize with weather, show the penalty does not increase as time in continuous maize increases (Meese et al., 1991; Crookston et al., 1991; Porter et al., 1997). A study based on farm survey data likewise found the penalty did not increase as the length of time of maize monoculture increased (Farmaha et al., 2016). To our knowledge, two Midwestern studies conclude the penalty increases as the number of years in a continuous maize system increases but one confounds weather with years-in-maize (Gentry et al., 2013) and the other uses satellite imagery (Seifert et al., 2017) that may likewise reflect confounding variables (**Figure** **5**).

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**Figure 7** Summary of literature investigating the relationship between the duration of continuous maize implementation and the continuous maize penalty, mean (dotted line) penalty in replicated studies (magenta) was 13%.

There is therefore strong evidence that considering only the previous year’s crop, rather than a multi-year history, is sufficient when considering driving factors for the continuous maize penalty. In the long-term, growing maize continuously compared to growing it in rotation with another crop may have long-term implications for soil characteristics such as organic carbon stocks, topsoil erosion, and weed pressure, which could conceivable amplify the continuous maize penalty over time. However, our dataset represents controlled small-plot experiments where weeds were controlled, erosion would have inconsistent effects across plots, and changes in soil carbon between the rotated- and continuous-maize systems at the highest N rates may be difficult to detect (Brown et al., 2014)

Our experimental data showed variation in the penalty is better explained by variation in the monoculture maize yields, suggesting it is indeed a yield *penalty* that is manifested through mechanisms present in the continuous maize system, rather than the rotated system driving an increase in yield potential. This is consistent with a study done in Minnesota that used fallow and chemical treatments and found the penalty is due to a negative effect of maize, not an enhancing effect of soybean (Crookston et al., 1988) Therefore, our efforts focused on understanding mechanisms in the continuous maize system that may limit the system’s expression of yield potential (Evans, 1996; van Wart et al., 2013).

Based on an extensive literature review we identified six general categories of candidate mechanisms for explaining the continuous maize penalty in the year following a maize crop (**Table** **3**).

**Table 3** General categories of mechanistic pathways by which growing maize following a maize crop results in lower grain yields under sufficient nitrogen inputs.

|  |  |
| --- | --- |
| **Hypothesis** | **Description** |
| Insufficient soil water recharge following maize | It is possible in some environments the soil water legacy of the previous year’s maize crop limits the amount of water available for the continuous maize system’s subsequent maize crop. |
| Delayed emergence | The high amounts of residue in continuous maize systems my result in cooler soil temperatures, which could delay seedling emergence. |
| Seedling death | Planting into soil with high amounts of maize residue may reduce seedling establishment by reducing seed to soil contact, through allelopathic effects, and/or through the residue creating physical barriers that impedes seedling growth and successful establishment. Additionally, higher amounts of residue may lead to cooler and wetter soils, which may result increase incidence of seedling disease. |
| Decreased early plant growth | More challenging early season conditions may lead to decreased early season plant growth, which would be expressed as a decrease in kernel number. |
| Foliar disease | When left on the soil surface, maize residue harbors inoculants for maize fungal diseases foliar diseases. Tillage is recommended to reduce inoculant amount but it is possible even small amounts of surface residue are sufficient to produce localized foliar diseases at a level that significantly affects maize yields. |
| Compromised root growth and/or function | Maize roots from the previous year may support higher levels of soil bacteria or mycorrhizal populations harmful to the following year’s maize roots. Additionally, while soil disease inoculants are always present in Corn Belt soils, cooler and wet soil conditions may result in less competition with other micro-organisms allowing disease to establish and cause higher incidences of root disease. |

### Scenario testing

Comparison of soil water dynamics at a 7 cm depth showed soil water content was as high or higher before maize planting following a maize crop compared to a soybean crop (supplemental material). This suggests that in Midwestern systems, the soil water profile is typically fully recharged following either a soybean or maize crop prior to the following spring.

We used the results from the literature review (**Table 3**) and statistical associations from the experimental data to build and test six modelling scenarios (**Table** **4**).

**Table 4** Model parameter adjustments to investigate feasibility of hypothesized mechanisms for the continuous maize penalty

|  |  |  |  |
| --- | --- | --- | --- |
| **Scenario** | **Target outcome** | **Parameter** | **APSIM implementation** |
| 1 | Seedling death | Lower plant population | Manually decreased plant population by 1 pl m-2 (from 8 to 7 pl ha-1) |
| 2 | Delayed emergence | Time from sowing to emergence | Changed sowing depth from 50 mm to 100 mm |
| 3 | Foliar disease-induced decrease in plant function | Decreased radiation use efficiency (RUE) | Reduced cultivar RUE  from 1.6 to 1.4 for emergence through flowering (Stage 5). |
| 4 | Compromised root growth | Root front velocity (RFV) | Decreased root\_depth\_rate at each stage by 50% to 2.5, 4.5, 17, 17, 15, 10 |
| 5 | Compromised root function | Root absorption efficiency | Decreased maize KL(/day) from 0.08 to 0.05 in all soil layers down to 120 cm |
| 6 | Decreased early plant growth | Decreased potential kernel number | Lowered head\_grain\_no\_max from 770 to 720 |

While results varied by site, delayed emergence (Scenario 2) produced consistently impractical results with regards to the continuous maize penalty, as shown in the results from site IA-3 (**Figure** **7**). Within error, all other scenarios had feasible effects on continuous maize yields. When all individual parameter changes were combined, the mean observed penalty was comparable to the experimentally observed penalty.

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**Figure 8** Site IA-3 experimentally observed penalties (yellow bars) with 95% confidence intervals (vertical lines) ordered from largest to smallest penalty size are compared to the baseline model parameter values (green bars), scenarios (Table 4), and a combination of scenarios excluding delayed emergence (Secnario 2; dark blue bars)

There is limited data available to corroborate the model’s identification of feasible pathways. While reduced plant number was a feasible scenario (Scenario 1), several multi-site and multi-year studies have not found significant differences in maize stand counts in monoculture and maize-soybean rotations (Griffith et al., 1988; Licht unpublished data).

Several studies suggest maize roots are indeed different in maize monocultures compared to rotated systems, but the form of that difference is not clear. A Wisconsin study showed more root length, as well as a higher percentage of necrotic roots, in maize monocultures compared to diverse rotations at 0-15 cm depths, with the authors hypothesizing the increased root length was a response to poor root health in maize monocultures (Goldstein, 2000). Additionally, the author found the monoculture maize had higher soil residual N at harvest compared to the maize-soybean rotation, suggesting that while N was available it may not have been captured by the maize plant due to compromised root function. A study done in Minnesota likewise found maize grown in a monoculture had higher root length densities in the top 0-12.5 cm, but had less root length density than maize rotated with soybean below that depth. Studies in Minnesota and Wisconsin showed higher populations of arbuscular mycorrhizae fungi in continuous maize compared to rotated maize that are negatively correlated with maize yields (Johnson et al., 1992; Chamberlain et al., 2021). Furthermore, a study in Wisconsin found soil fumigation can significantly reduce the continuous maize penalty, suggesting the effect is highly biological (Turco et al., 1990), and would be manifest through effects on plant roots. Previous studies in Ohio and Indiana found the penalty was higher in poorly-drained sites (Dick and Doren, 1985; Griffith et al., 1988), which is consistently with the hypothesis of soil disease being magnified by maize monoculture and wet environments.

Surface residue has well-documented effects on the incidence of foliar diseases in maize (Robertson and Munkvold, 2007a; b), but to our knowledge there are no studies that have explicitly linked maize surface residue amounts to the continuous maize penalty. The relationship may be complex, as disease severity relies not only on inoculum but on environmental conditions as well. Furthermore, rather than a simple linear relationship, it is possible there is bi-linear pattern wherein a threshold surface residue amount needed before the environmental conditions can foster increased disease incidence in continuous maize. Lastly, small plot research may create conditions where residue may provide inoculum to spread to other rotation treatments. Information on surface residue amounts in long-term rotation experiments could help parse out these relationships.

To our knowledge there are no growth analysis comparisons of maize grown in monoculture compared to in rotation, nor comparisons of yield components of maize grown in the two systems. Therefore, while reduced potential kernel number from lower rates of early season maize growth is feasible, there is limited experimental data to support or refute it as a driver of the penalty.

In addition to APSIM’s predictions that delayed germination is an unlikely consistent driver of the penalty, field studies likewise show negligible effects of maize residue on maize plant germination timing versus soybean residue (Kaspar et al., 1990; Shen et al., 2018).

### Dynamic script testing

The analysis of the experimental data indicated site-by-year interactions are a major contributor to variation in the observed penalty. We therefore implemented scripts to dynamically change parameter values based on surface residue amounts, soil temperature tracking, and soil moisture tracking (supplemental material). However, we found it difficult to assess whether this improved model predictions because of the uncertainty around the measured penalty sizes. While the mean observed penalty was 1.0 Mg ha-1, the average standard deviation for the sites where that information was available was 0.7 Mg ha-1. Therefore, while the dynamic implementation of penalties in the model affected the predicted penalty, and in many cases improved the overall site-average prediction of the penalty (supplementary material), the size of the penalty was not known with enough precision to identify the optimal script parameters for capturing the year-to-year variation.

# Synthesis

This study used APSIM as a tool to understand a well-described but poorly understood phenomenon, the continuous maize penalty, which impacts approximately one-third of the US Corn Belt. Long-term field data indicated the penalty has remained constant over two decades of farming, and that in most cases (>95%) the penalty cannot be overcome with additional N fertilization. Based on the available literature, our experimental data, and the modelling exercises there is strong evidence the amount of residue alone cannot account for the penalty; future research should focus on understanding interactions of residue and possible non-linear relationships. Measurements of residue inputs and surface residue at planting would aid in understanding the role of residue in the penalty. Our study found cold wet soils are associated with higher penalties, conditions that may favor soil-borne diseases (Crop Protection Network,) and may compromise the continuously grown maize root system’s ability to acquire resources. While the modelled results demonstrate several feasible mechanisms, without data to support or refute them all are reasonable implementations of the continuous maize penalty in models. Growth analyses and yield components of maize in the two systems would provide insight into whether the penalty is most pronounced during a particular phase of growth, or whether the timing of the effect varies by year. Additionally, measurements of the root front velocity (Ordóñez et al., 2018) and root length and biomass at flowering (Ordóñez et al., 2021) would provide much-needed information on differences in root functioning in the two cropping systems.

Our study has implications for models and crops in addition to maize. Many crops exhibit lower yields when grown continuously (Bennett et al., 2012), and our study provides a framework for understanding driving mechanism in crops such as wheat, soybean, and rice. Models used for N recommendations should incorporate the continuous maize penalty, and our study indicates accurate recommendations will depend on the model’s ability to account for factors that inhibit the ability of continuous maize to respond to additional N inputs such as impaired root function. Through a synthesis of current knowledge and by leveraging the APSIM model, our study has advanced the state of knowledge regarding the continuous maize penalty and provided a pathway for future research to address remaining knowledge gaps regarding the mechanisms driving the continuous maize penalty.

# Supplementary Material

## Figures

### **Figure S1.** Summary of continuous maize penalty relative to rotated-maize yields at seven Iowa locations as a function of tillage type. Data was extracted from Al-Kaisi et al. 2015.

Chart, line chart

Description automatically generated

### Figure S2. Variance decomposition of penalty components and relationship between N-compensatable and observed yield penalties

Chart, scatter chart

Description automatically generated

### Figure S3. Continuous maize penalty by year

Chart, box and whisker chart

Description automatically generated

### **Figure S4.** Calibrated APSIM model predicted soil water dynamics in maize phase of continuous- and rotated-maize cropping systems at four sites over 16 years

Chart, histogram

Description automatically generated

### Figure S5. Improvement in APSIM maize yield predictions with inclusion of dynamic scripts

XX

## Tables

### Table S1. Experimental site information

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Site ID** | **Latitude, longitude** | **Nearest town** | **Seasons of data** | **Nitrogen rates**  **(kg ha-1)** | **Tillage** | **Average CRM** |
| *Iowa Sites* | | | | | | |
| IA-1 | 42.93,  -95.54 | Sutherland, IA | 17 | 0, 45, 90, 135, 180, 225, **270** | Conventional† | 103 |
| IA-2 | 42.91,  -93.79 | Kanawha, IA | 12 | 0, 45, 90, 135, 180, 225, **270** | Conventional | 102 |
| IA-3 | 42.93,  -92.57 | Nashua, IA | 12 | 0, 45, 90, 135, 180, 225, **270** | Conventional | 105 |
| IA-4 | 42.02,  -93.78 | Ames, IA | 18 | 0, 68, 135, 203, **270** | Conventional | 106 |
| IA-5 | 41.31,  -95.18 | Lewis, IA | 16 | 0, 45, 90, 135, 180, 225, **270** | Conventional | 111 |
| IA-6 | 40.97,  -93.42 | McNay, IA | 18 | 0, 45, 90, 135, 180, 225, **270** | Conventional | 112 |
| IA-7 | 41.19,  -91.48 | Crawfordsville, IA | 18 | 0, 45, 90, 135, 180, 225, **270** | Conventional | 111 |
| *Illinois Sites* | | | | | | |
| IL-1 | 41.84,  -88.86 | Dekalb, IL | 10 | 0, 51, 101, 152, 203, **253** | Conventional | 109 |
| IL-2 | 40.93,  -90.73 | Monmouth, IL | 10 | 0, 51, 101, 152, 203, **253** | Conventional | 113 |
| IL-3 | 39.80,  -90.82 | Orr Center, IL | 10 | 0, 51, 101, 152, 203, **253** | Conventional | 113 |
| IL-4 | 40.08,  -88.22 | Urbana, IL | 10 | 0, 51, 101, 152, 203, **253** | Conventional | 112 |
| IL-5 | 38.95,  -88.96 | Brownstown, IL | 8 | 0, 51, 101, 152, 203, **253** | No-till | 114 |
| IL-6 | 37.46,  -88.72 | Dixon Springs, IL upland area | 10 | 0, 51, 101, 152, 203, **253** | No-till | 113 |
| IL-7 | 37.42,  -88.66 | Dixon Springs, IL lowland area | 10 | 0, 51, 101, 152, 203, **253** | No-till | 113 |
| †Conventional tillage consisted of chisel plowing in the fall following harvest and field cultivation in the spring for all phases of all crop rotations. | | | | | | |

### Table S2. List of predictors included in feature selection models

Insert table, I know I made it it’s just on my dang office computer I guess I didn’t commit/push.

### Table S3. Calibration statistics for APSIM models

Waiting for poor Mitch.

## Text

### Text S1. Description of dynamic APSIM scripts

Table S5. List of literature references

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