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Deteriorating weed control and variable weather portends greater soybean yield losses in the future

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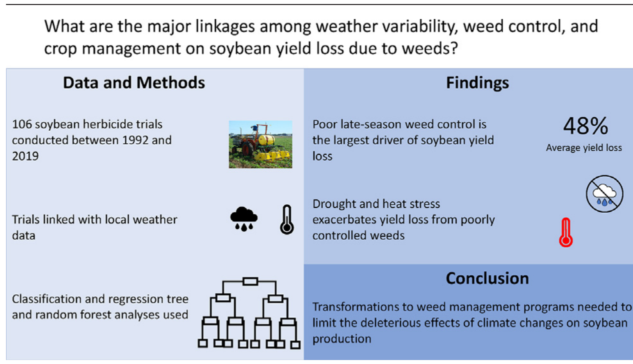
HIGHLIGHTS

- Poor late-season weed control is the major driver of soybean yield loss.
- Later maturing cultivars alleviate some of the yield loss from late-season weeds.
- Drought or heat stress exacerbates yield loss from late-season weeds.
- Drought and heat stress are especially damaging during reproductive growth.

GRAPHICAL ABSTRACT



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ABSTRACT

Since the 1950's much of the US soybean growing region has experienced rising temperatures, more variable rainfall, and increased carbon emissions. These trends are predicted to continue throughout the 21st century. Variable weather and weed interference influence crop performance; however, their combined effects on soybean yield are poorly understood. Using machine learning techniques on a database of herbicide trials spanning 28 years and 106 weather environments we modeled the most important relationships among weed control, weather variability, and crop management on soybean yield loss. When late-season weeds were poorly controlled, average soybean yield losses of 48% were observed. Additionally, when weeds were not completely controlled, low rainfall and high temperatures during seed fill exacerbated soybean yield loss due to weeds. Since much of the US soybean growing region is heading towards drier, warmer conditions, coupled with growing herbicide resistance, future soybean yield loss will increase without significant improvements in weed management systems.

1. Introduction

The US produces over 31% of the global soybean (*Glycine max* (L.) Merr) supply (USDA-FAS, 2021). Currently, soybean is grown on 30 million ha in the US with a farmgate value exceeding $31 billion (USDA-NASS, 2021). However, soybean production is impacted by variability in climate factors such as CO_2 levels, temperature, and rainfall. These climate factors account for 20% and 15% of the variability in global and North American soybean yield, respectively (Vogel et al., 2019).

Future climate changes are expected to further threaten the stability of US soybean production (IPCC, 2019). Much of the US soybean growing region is expecting a 2.6 to 5.2 °C increase in average air temperature (Hayhoe et al., 2018). Furthermore, an increase in the frequency of daily high temperatures exceeding 35 °C is expected over the same period (Seneviratne et al., 2012). Warming air temperatures will cause a gradual

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soybean yield increase up to a threshold temperature of 30 °C; however, for every 1 °C increase in daily average temperature above 30 °C, yield losses of 16% can occur (Kucharik and Serbin, 2008; Lobell and Asner, 2003; Lobell and Field, 2007; Schlenker and Roberts, 2009). Excessive temperatures are especially damaging during soybean reproductive growth stages, leading to flower or pod abortion and reduced seed fill (Egli and Wardlaw, 1980; Puteh et al., 2013). A slight increase in spring rainfall, occurring mainly from increased frequency of extreme rainfall events, is expected for much of the US soybean growing region (Hayhoe et al., 2018; Romero-Lankao et al., 2014). Higher frequency of extreme rainfall events can decrease the number of field working days and delay planting and crop emergence (Tomasek et al., 2017). Additionally, extreme rainfall events may lead to flooding, which is deleterious to soybean within 48 h of planting (Urban et al., 2015; Wuebker et al., 2001). Reduced summer rainfall and an increase in drought frequency and severity are likely to accompany the increased spring rainfall (Hayhoe et al., 2018; Jin et al., 2018). Damage to soybean yields from drought stress will vary by both the timing and severity of the drought, with flowering and seed fill being the most susceptible stages (Cui et al., 2019; De Souza et al., 1997; Heatherly, 1993; Siebers et al., 2015; Wijewardana et al., 2018).

Average atmospheric CO_2 concentrations are currently greater than 400 ppm and, under most greenhouse gas emissions scenarios, are expected to rise above 550 ppm by the end of the century (Hayhoe et al., 2018). Increased concentrations of CO_2 improve yield in C_3 plants such as soybean via CO_2 fertilization, which is thought to result from stimulation of photosynthesis, and reduction in stomatal conductance and transpiration (Bernacchi et al., 2005; Drake et al., 1997; Jin et al., 2018; Leakey et al., 2009). However, both excessive temperature and drought stress during reproductive growth have been shown to reduce or eliminate the benefits of CO_2 fertilization (Jin et al., 2018, 2017; Thomey et al., 2019).

Even under ideal environmental conditions, soybean production is threatened by interference from uncontrolled weeds. The potential for soybean yield loss due to weeds in the US stands at $16.2 billion (Soltani et al., 2017). Irreversible soybean yield loss due to weed interference can occur as early as the first trifoliate stage (Green-Tracewicz et al., 2012; Van Acker et al., 1993). Weeds negatively affect soybean production by disrupting harvest operations (Nave and Wax, 1971), altering seed protein content (Gibson et al., 2008), and competing for limited resources such as light and nutrients throughout the growing season (Burnside, 1973). Although weeds and weather variability are concomitant stressors of soybean, little is known about their combined effects on soybean production. A better understanding of how soybean responds to climate change and weed interference can be useful in developing strategies to mitigate the impact of climate in the future.

The most common method for controlling weeds in soybean is the use of preemergence (PRE) and postemergence (POST) herbicides. In the US, 99% of all soybean hectares were treated with at least one herbicide application (USDA-NASS, 2021). Herbicide efficacy varies depending on the product, application timing, soil characteristics, target weed species, and environment. Inadequate rainfall following PRE application increases the risk of unsuccessful weed control of soil-residual herbicides (Landau et al., 2021a). In contrast, excessive rainfall can leach certain PRE herbicides out of the weed seedling emergence zone, thereby preventing lethal doses from being absorbed by target weeds (Ziska, 2016). Warmer temperatures (e.g. >30 °C) increase the growth rate of several weed species, thereby reducing the window of time for effective application of many POST herbicides (Guo and Al-Khatib, 2003; Patterson, 1995). Additionally, herbicide uptake and metabolism by crop and weed species are positively correlated with air temperature for several herbicides (Bailey, 2003; Johnson and Young, 2002).

The growing prevalence of herbicide resistance is reducing the utility of chemical weed control. Within the US, weed populations from at least 24 species have evolved resistance to herbicides across 10 of the 14 sites of action labeled in soybean (Heap, 2021). More concerning is that seven of these species have evolved multiple herbicide resistance (resistance to two or more herbicides from different sites of action within the same population) and are commonly found in soybean fields. Growers expect new herbicides will alleviate the problems caused by herbicide resistance (Schroeder et al., 2018); however, herbicide discovery has stagnated for decades primarily due to the increased costs of bringing new herbicides to the market and increased regulatory requirements (Sparks and Lorsbach, 2017). As such, non-chemical weed management tactics such as changing crop management strategies to increase soybean's competitiveness with weeds will need to be further explored to mitigate some of the impacts from increasing resistance issues.

The major hindrance to adequately examining the linkages among climate variability, weed control, and crop management as they relate to soybean yield is often the relatively low number of environments (e.g., generally less than six) to draw inferences from. As such, the true linkages may not be adequately identified. This study utilizes machine learning techniques on a dataset of 106 herbicide trials conducted in Illinois, the largest soybean producing state in the US (USDA-NASS, 2021), to better characterize the interactions among soybean production, climate change, weed interference, and crop management practices. A better understanding of these interactions will assist soybean producers adapt to a changing climate. The objective of this study was to identify the major linkages among weather variability, weed control, and crop management on soybean yield. We hypothesize that soybean yield loss due to weeds is primarily driven by incomplete weed control paired with drought stress or heat stress during the reproductive growth stages.

2. Materials and methods

2.1. Field trial description

The Herbicide Evaluation Program (HEP) at the University of Illinois conducted >1500 herbicide evaluation trials in soybean between 1992 and 2019. Most trials were conducted in Urbana, IL (40°4′31″N/ 88°14′31 W), where the soil types were either a Flanagan silt loam (fine, smectitic, mesic Aquic Argiudolls) or a Drummer silty clay loam (fine-silty, mixed, mesic Typic Endoaquolls) with an average pH of 6.4 and 4.9% organic matter. Each trial consisted of herbicide, spray adjuvant, and weedy control treatments. Treatments were arranged in a randomized complete block design with three replicates. Data varied by trial but often included percent weed control (0% is no control, 100% is complete control) of dominant species up to five times during the growing season, percent soybean injury (0% is no injury, 100% is crop death), and occasionally soybean yield. Soybean cultivar, planting date, planting density, and previous crop were recorded. Data from each trial were compiled into a single database (hereafter referred to as the HEP database) using FieldPro: Bio Data Management Software (Heartland Technologies, INC., 12491 E. 136th St., Fishers Indiana).

2.2. Database management

The HEP database was initially filtered to contain only trials with both weed control ratings and soybean yield. Trials not conducted in Urbana, IL were removed due to low numbers of observations. One early-season (21–42 days after planting) and one late-season (63–84 days after planting) weed control rating were used for each treatment within each trial in order to compare trials across similar time points. Season-long weed control was calculated as the average of the early and late-season weed control ratings.

Many trials within the HEP contained notes on when the crop reached the R5 growth stage (i.e. beginning seed) (Naeve, 2018). Unpublished soybean cultivar trials in Urbana, IL were used to estimate the R5 date in trials missing such data (pers. comm. E. Nafziger). Five consecutive 21-day intervals were created for each trial, with the fourth interval (hereafter referred to as seed fill) centered at the R5 date. Other intervals corresponded to the following soybean growth stages; early-vegetative growth (interval 1), late-vegetative growth (interval 2), flowering to pod development (interval 3), and full maturity (interval 5). Average air temperature, total rainfall, and potential evapotranspiration (PET) were added for each interval, and data was provided by the Illinois State Climatologist's Office (a part of the Illinois

State Water Survey located in Champaign and Peoria, Illinois, and on the web at www.sws.uiuc.edu/atmos/statecli). Cumulative growing degree days (GDDs) and total water balance were calculated and added for each interval. Average vapor pressure deficit (VPD) was calculated for each 21-day interval using the following equation (Monteith and Unsworth, 2008).

$$\mathrm{VPD_{int}} = \left(0.611 * \exp\left(\frac{\mathrm{T_{avg}} * 17.3}{\mathrm{T_{avg}} + 237.3}\right)\right) * \left(1 - \left(\frac{\mathrm{RH_{avg}}}{100}\right)\right) \quad (1)$$

where T_{avg} and RH_{avg} are the average temperature and relative humidity respectively over the 21-interval.

Large variation in season-long weather was observed across the 106 environments from 28 years of data. Average season-long precipitation was 472 mm with a minimum of 295 mm in 2013 and a maximum of 914 mm in 1993 (Table 1). Average season-long PET ranged from 418 mm in 2009 to 765 mm in 2007 with an average PET of 639 mm. Season-long GDD accumulation varied by year and planting date, ranging from 1399 to 1929 GDD's. Average VPD over the 21-day interval ranged from 0.21 and 1.40 kPa.

Within each trial, weed-free yield was added to each treatment and was calculated as the average yield of each treatment within the trial with ≥95% control for all evaluated weed species. Trials that did not contain any treatment with ≥95% were removed from the database. Following the filtering and removal processes, the database contained 106 trials and 1092 observations. For each treatment within each trial, percent yield loss was calculated using the following equation.

$$\text{percent yield loss} = \frac{\text{trial weedfree yield} - \text{individual treatment yield}}{\text{trial weedfree yield}} * 100 \quad (2)$$

For each weed in the HEP database, competitive index (CI) values were extracted from WeedSOFT Decision Support System (University of Nebraska-Lincoln, P.O. Box 830915, Lincoln, NE). These CI values were developed using local or regional research as well as expert opinions (Neeser et al., 2004). Values for CI are scaled and calculated relative to the most competitive weed species with soybean using the following equation (Coble and Mortensen, 1992):

$$\mathrm{CI_i} = \frac{\mathrm{P(i)}}{\mathrm{P(m)}} * 10 \quad (3)$$

where CI_i is the competitive index of weed i, $P(i)$ is the percentage of soybean yield loss caused by a low density of weed i, and $P(m)$ is the percentage of soybean yield loss caused by low levels of the most competitive weed species. Because the values are scaled, CIs range from 0.0 to 10.0 with 0.0 being the least, and 10.0 being the most competitive with soybean. The CIs do not account for weed population density; as such, sufficient densities of a low CI weed (e.g., 1.0) can be detrimental to the crop. Five of the seventeen weed species in the database did not have a reported CI for soybean in IL; therefore, CIs of related or comparable species were used. The weeds in the HEP database were then grouped based on their competitive index with each group spanning 1.0 CI. A list of the weed species observed in this study, including their CI and CI group, is reported in Table 2.

Throughout the 28 years of soybean herbicide evaluation trials, percent weed control varied greatly and was dependent on weed species. All CI groups had a minimum and maximum recorded percent control of 0 and 99%, respectively (Table 1). The CI-0 group had the highest average season-long weed control (mean = 91%) and was mainly composed of henbit (*Lamium amplexicaule* L.) and common chickweed (*Stelaria media (L.) Vill.*). The CI-8 group had the lowest mean season-long control (mean = 75%) and consisted of only common cocklebur (*Xanthium strumarium* L.).

Several soybean management practices were captured within the database. Forty-five unique cultivars were used throughout the 28 years of trials. These cultivars were planted between April 28 and June 29 (Table 1). Planting densities of these cultivars ranged from 346,000 to 544,000 plants ha^{-1} and was consistent with soybean planting densities for Illinois between 1992 and 2019.

2.3. Statistical analysis

Classification and regression tree (CART) analysis was used in order to visually model the relationship among weed control, weather, and soybean management practices on both soybean yield and soybean yield loss due to weeds. Random forest analysis was used to determine the importance of each independent variable for predicting soybean yield and yield loss. Random forest and CART provide advantages over other traditional statistical methods. For example, as both techniques are nonparametric, there are no underlying assumptions of the data distributions. Additionally, both models can handle incomplete or missing data, as well as data from numerous quantitative and qualitative variables.

The CART procedure was implemented using the *rpart* package in R (Therneau and Atkinson, 2019). The CART model separates the dependent variable into two groups (nodes) using continuous and categorical independent variables as splitting points (Breiman et al., 1984). Threshold values for each splitting point were selected by the model based on the data distribution. The minimum number of observations required for the CART algorithm to attempt to split the data was set to 50 and the minimum number of observations required to be in any terminal leaf following a split was set to 15. Independent variables were selected by the model only if they minimized the heterogeneity of the dependent variable. The final CART model is displayed as an easily interpretable dichotomous tree. To obtain the most parsimonious model, the dichotomous tree was pruned using the "1-se" rule, which selects the simplest model within one standard error of the model with the lowest error value.

The random forest analysis was implemented using the *randomForest* package in R (Liaw and Wiener, 2002). The random forest algorithm creates one model by creating and combining numerous regression trees. The individual trees were created similar to the CART analysis, with each tree being constructed using a random subset of observations and independent variables. The number of individual regression trees created by the random forest algorithm was set to 500 and the number of independent variables randomly selected as candidate for each split in the trees was set to 17. Additionally, the minimum number of observations in each terminal node was set to 5. Each subset was split into a training set from which the tree is developed, and a hold-out set used to test the tree. For each tree, the mean-squared error (MSE) was calculated from the hold-out set of data (Breiman, 2001). The MSE was then recalculated for the individual trees after permuting each independent variable. Variable importance was calculated as the difference between both MSEs averaged across all

Table 1
Summary statistics of season-long weed control, season-long total thermal time and precipitation, and agronomic variables from soybean yield trials conducted in Urbana, Illinois from 1992 to 2019. Explanation of abbreviations: CI-0 to CI-8, average control of all weed species grouped by their respective competitive index (i.e. CI-0 includes all weeds with a competitive index of 0.0–0.9); GDD, growing degree day; PET, potential evapotranspiration; VPD, average vapor pressure deficit for the 21-day growth intervals; DOY, day of year.

	Unit	Mean	Min	Max
Season-long control				
CI-0	%	91	0	99
CI-1	%	84	0	99
CI-2	%	83	0	99
CI-3	%	76	0	99
CI-8	%	75	0	99
All weed species	%	80	0	99
Season-long total				
Thermal time	GDD	1668	1399	1929
Precipitation	mm	472	295	914
PET	mm	639	418	765
VPD	kPa	0.73	0.21	1.40
Agronomic variables				
Planting date	DOY	142	118	180
Planting density	plants ha^{-1}	398,000	346,000	544,000

Table 2
Competitive index (CI) and CI group of weed species observed in the Herbicide Evaluation Program database. The CI of each species in soybean was obtained from WeedSOFT Decision Support System (University of Nebraska-Lincoln, P.O. Box 830915, Lincoln, NE).

Competitive index group[a]	Common name	Scientific name	Competitive index	Number of observations
CI-0	[b]Henbit	*Lamium amplexicaule* L.	0.5	75
	Eastern black nightshade	*Solanum ptychanthum* Dunal	0.5	28
	[b]Common chickweed	*Stellaria media* (L.) Vill.	0.5	97
CI-1	[b]Horseweed	*Erigeron canadensis* L.	1.0	172
	Giant foxtail	Setaria faveri Herm.	1.0	911
	[b]Common dandelion	*Taraxacum officinale* F. H. Wigg	1.0	60
	Ivyleaf morningglory	Ipomea hederacea Jacq.	1.5	72
	Tall morningglory	Ipomea purpurea (L.) Roth	1.5	539
CI-2	Velvetleaf	*Abutilon theophrasti* Medik	2.0	661
	Common ragweed	*Ambrosia artemisiifolia* L.	2.0	124
	Pennsylvania smartweed	Persicaria pensylvanicum (L.) M. Gomez	2.0	220
	Smooth pigweed	*Amaranthus hybridus* L.	2.5	114
CI-3	[b]Palmer amaranth	*Amaranthus palmeri S. Watson*	3.0	59
	Waterhemp	*Amaranthus tuberculatus* (Moq.) J.D. Sauer	3.0	511
	Jimsonweed	*Datura stramonium* L.	3.0	47
	Common lambsquarters	*Chenopodium album* L.	3.5	584
CI-8	Common cocklebur	*Xanthium strumarium* L.	8.0	141

[a] Species were grouped by the range of competitive indices. For example, CI-0 contains the tested species with a competitive index in soybean between 0.0 and 0.9. No tested weed species had a competitive index ranging between 4.0 and 7.9, as such, there is no CI-4, CI-5, CI-6, or CI-7 groups.
[b] Species does not have a listed CI; as such, the CI of a comparable species was used.

trees, normalized by the standard error. Variables with higher variable importance are more influential in predicting the dependent variable. The 52 independent variables used in the CART and random forest analyses are reported in Table 3.

3. Results

Late-season average control of all species and season-long control of all species were identified by the random forest analysis as the two most important variables for predicting soybean yield loss due to weeds (Fig. 1). The additional selected variables included late-season control of the CI-2 and CI-3 group weeds, soybean maturity group, soybean injury, and VPD, average temperature, maximum temperature, and total rainfall during seed fill. The final model explained 75% of the variability in soybean yield loss due to weeds.

Table 3
List of independent variables used in machine learning techniques. Explanation of abbreviations: PRE, preemergence; POST, postemergence.

Variable group	Variables
Early-season weed control	Average control of all species (%)
	Average control of each competitive index (CI) group (CI-0 to CI-8)
Late-season weed control	Average control of all species (%)
	Average control of each CI group
Season-long weed control	Average control of all species (%)
	Average control of each CI group
Air temperature	Season-long, daily thermal time (GDD)
	Maximum temperature during early-vegetative growth, late-vegetative growth, flowering to pod development, seed fill, and full maturity (°C)
	Average temperature during early-vegetative growth, late-vegetative growth, flowering to pod development, seed fill, and full maturity (°C)
Water	Total precipitation during early-vegetative growth, late-vegetative growth, flowering to pod development, seed fill, and full maturity (mm)
	Potential evapotranspiration (PET) early-vegetative growth, late-vegetative growth, flowering to pod development, seed fill, and full maturity (mm)
	Water balance during early-vegetative growth, late-vegetative growth, flowering to pod development, seed fill, and full maturity (mm)
	Average vapor pressure deficit (VPD) early-vegetative growth, late-vegetative growth, flowering to pod development, seed fill, and full maturity (kPa)
Crop management	Cultivar information (i.e., name, maturity group, year of introduction)
	Previous crop
	Planting density (plants ha^{-1})
	Planting date
	Crop injury (%)
	Herbicide treatment timing (i.e., PRE, POST, PRE + POST)

The most parsimonious CART model constructed for soybean yield loss due to weeds included six nodes with four of the 52 possible independent variables; late-season average control of all species, soybean maturity group, total rainfall during seed fill, and maximum temperature during seed fill (Fig. 2). The model explained 60% of the variability in yield loss due to weeds. The highest yield losses (mean = 52%) occurred when late-season average control of all species was <51% in a maturity group <3.6. The lowest yield loss levels (mean = 3%) occurred when late-season average control of all species was ≥94%.

Similar to soybean yield loss, late-season average control of all species was identified as the most important variable for predicting soybean yield. Additionally, the yield random forest model included six important variables identified by the yield loss random forest model: season-long average control of all species, CI-3 late-season control, and VPD, average temperature, maximum temperature, and total rainfall during seed fill (Fig. 3). The other important variables identified by the model were VPD and average temperature during early vegetative growth and total rainfall during late vegetative growth. The random forest model explained 88% of the variability in soybean yield. The most parsimonious CART model for soybean yield explained 70% of the variability in soybean yield and included six nodes and six of the 52 possible independent variables (Fig. 4). The variables selected by the CART model were also selected in the ten most important variables by the random forest model. The lowest yields (mean = 2068 kg ha^{-1}) occurred when late-season average control of all species was <88% and total rainfall during seed fill was <58 mm. The conditions leading to the highest soybean yields (mean = 4385 kg ha^{-1}) were late-season average control of all species ≥88%, VPD during early vegetative growth <0.95 kPa, maximum temperature during seed fill <30 °C, and mean temperature during early vegetative growth ≥20 °C.

4. Discussion

Both CART and random forest models selected late-season control of all weed species as the most important driver of soybean yield loss due to weeds. Treatments that provided poor late-season control (<51%) had an average yield loss of 48% (Fig. 2). Poor or no late-season weed control has been shown to cause up to 43% yield loss in soybean (Barrentine,

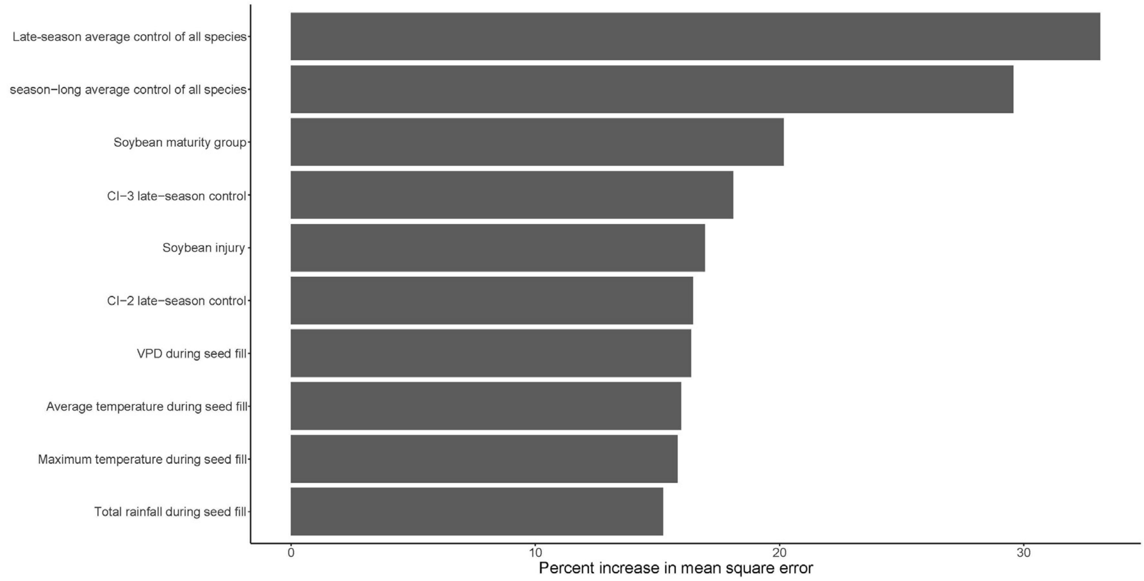

Fig. 1. Random forest variable importance for predicting soybean yield loss due to weeds. Larger percent increase in mean-squared error indicates a larger contribution of that variable for accurately predicting soybean yield loss due to weeds. Only the top ten variables from those analyzed (Table 3) are shown. The model explains 75% of variability in soybean yield.

1974; Hager et al., 2002). Additionally, results from the current study are consistent with a recent multi-state study showing 52% and 61% potential yield loss from uncontrolled weed species in the US and Illinois, respectively (Soltani et al., 2017).

Later maturing soybean cultivars alleviated some of the yield losses caused by poor late-season weed control. Maturity groups 3.6 or higher had an average of 16% less yield loss compared to earlier maturity groups. Compared to earlier maturity soybean, improved crop tolerance to weed interference with later soybean maturity groups was driven by increased competition for light (Nordby et al., 2007; Rose et al., 1984). Results from the current study suggest using later soybean maturity groups may be useful as part of an integrated weed management strategy to reduce the risk of incomplete weed control in the future as climate becomes more variable in the major soybean growing regions.

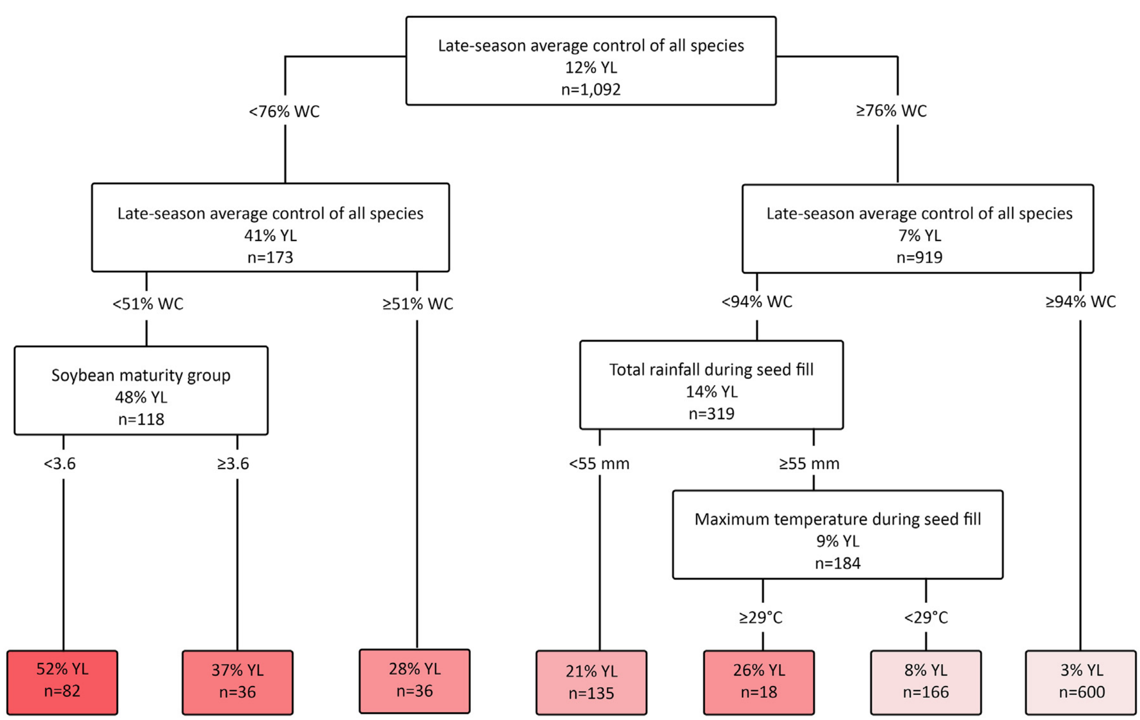

Fig. 2. Final classification and regression tree for soybean yield loss due to weed interference. Mean yield loss and the number of observations are reported under each node and each leaf. A total of 1092 observations obtained from trials conducted between 1992 and 2019 were used to create the final tree model. The model explains 60% of variability in soybean yield. Abbreviations: % YL, percent yield loss due to weeds; % WC, percent weed control.

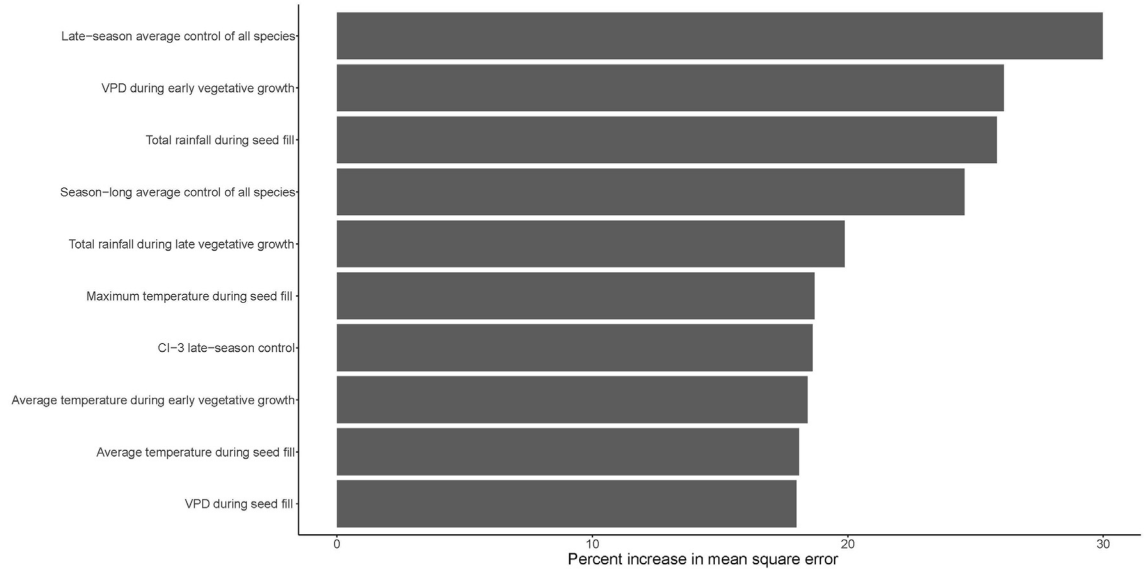

Fig. 3. Random forest variable importance for predicting soybean yield. Larger percent increase in mean-squared error indicates a larger contribution of that variable for accurately predicting soybean yield. Only the top ten variables are shown from those analyzed (Table 3). The model explains 88% of variability in soybean yield.

As hypothesized, yield loss due to weeds is driven by incomplete weed control coupled with drought and heat stress during soybean reproduction. Furthermore, the period of soybean seed fill was particularly vulnerable. When the highest level of weed control was not achieved, treatments with lower rainfall (<55 mm) during seed fill had an average 21% yield loss compared to 9% yield loss with greater rainfall (Fig. 4). Several weed species in US cropping systems display increased competitiveness with soybean for water under drought stress conditions (Patterson, 1995). For instance, waterhemp persisted under severe drought stress and showed increased injury to soybean (Sarangi et al., 2016).

Furthermore, in treatments with rainfall ≥55 mm, maximum temperatures ≥29 °C during seed fill had on average 26% yield loss compared to 8% yield loss when maximum temperatures were moderate. A similar trend was recently reported for maize (*Zea mays* L.) where warmer temperatures and drought conditions during silking exacerbated the yield loss from uncontrolled or poorly controlled weeds (Landau et al., 2021b). In the present study, the combination of heat stress, drought stress, and larger more competitive weeds was likely the cause of the increased yield loss. High air temperatures have been shown to increase dry matter accumulation of Palmer amaranth (*Amaranthus palmeri* S. Wats) by up to 1600%

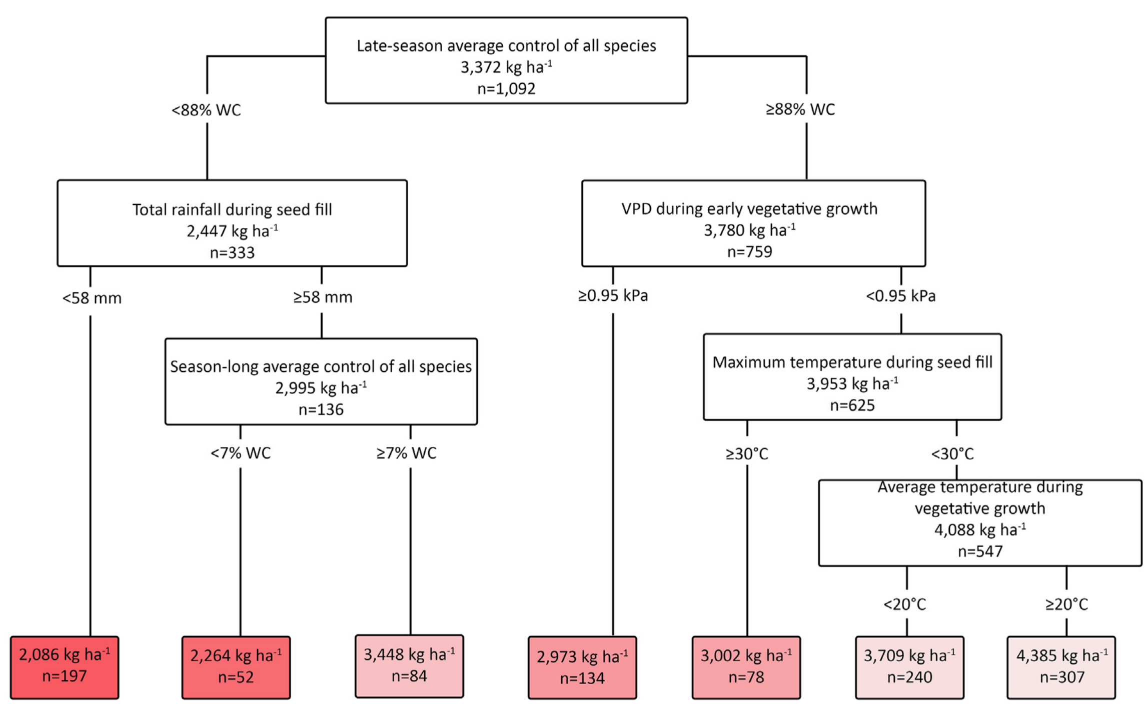

Fig. 4. Final classification and regression tree for soybean yield. Mean yield and the number of observations are reported under each node and each leaf. A total of 1092 observations obtained from trials conducted between 1992 and 2019 were used to create the final tree model. The model explains 70% of variability in soybean yield. Abbreviations: % WC, percent weed control; VPD, vapor pressure deficit.

compared to more moderate temperatures, while soybean showed a 10–20% decrease in dry matter accumulation (Wright et al., 1999). Similar growth stimulation at higher temperatures also has been observed in waterhemp (Guo and Al-Khatib, 2003), green foxtail (*Setaria viridis* L.) (Wall, 1993), and velvetleaf (*Abutilon theophrasti* Medic.) (Patterson et al., 1988). Results from the current study offer a window into how hotter, drier conditions increase the risk of soybean yield loss from sub-optimal weed control. Improvements to soybean weed management strategies need to be made in order to limit the risk of yield loss from more variable future weather.

Early vegetative growth of soybean is not immune to arid weather. Prolonged high VPD ($\geq$0.95 kPa) during the early vegetative growth stages caused an average 958 kg ha^{-1} reduction in yield (Fig. 4). While not as susceptible as the reproductive stages, soybean vegetative growth is affected by drought stress and significant yield damage can occur if the stress is severe (Cui et al., 2019). Decreased photosynthetic ability, leaf growth, and shoot growth as early-season drought stress increased have been reported in soybean (Wijewardana et al., 2019). The current study highlights the need for adequate moisture not only during reproductive growth, but during vegetative growth stages as well in order to maximize soybean yields. However, as rainfall becomes more variable, and droughts become more prevalent throughout the coming century, the risk of reduced yield caused by drought stress will increase unless crop management practices, such as drought-tolerant cultivars or irrigation, are adopted.

Much of the US soybean growing region is expected to have warmer temperatures and more variable precipitation patterns throughout the coming century. The region will experience up to a 5 °C increase in average yearly air temperature accompanied by drier summers and higher chances for drought (Hayhoe et al., 2018; Romero-Lankao et al., 2014). These weather changes are likely to expose soybean to heat stress and drought stress during the reproductive growth stages. Both drought and heat stress during flowering or seed fill cause significant soybean yield loss and can negate the expected benefits from CO_2 fertilization (Cui et al., 2019; Jin et al., 2018, 2017). These projected weather changes will also increase the growth rate and competitiveness of many common weed species, and reduce the efficacy of commonly used herbicides (Guo and Al-Khatib, 2003; Landau et al., 2021a; Patterson, 1995). Results from the current study foreshadow a grim future for soybean production in a more variable climate unless improvements to late-season weed control are made.

By analyzing a database of herbicide evaluation trials spanning 106 weather environments and > 1000 observations, this research provides the most in-depth assessment of the combined effects of weed control, weather variability, and management practices on soybean yield response. The use of the machine learning techniques, CART and random forest, allowed for the identification of the most important weather, weed control, and crop management variables for predicting soybean yield loss due to weeds and soybean yield, while also displaying the results in an easily interpretable manner. Excellent weed control throughout the season is essential for avoiding yield loss due to weeds; however, achieving such a high level of weed control is becoming ever more difficult due to the increased prevalence of herbicide resistance. When weeds are not completely controlled, drought and heat stress during seed fill exacerbate yield loss. Current climate predictions portend a future with hotter, drier summers throughout much of the US soybean growing region. The development and adoption of higher efficacy weed management strategies will be essential in adapting soybean production systems to climate change. Such systems will likely rely on a combination of cultural, mechanical, biological, and chemical control strategies, perhaps including crop traits such as drought- and heat-tolerance.

CRediT authorship contribution statement

C. Landau: Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft **A. Hager**: Conceptualization, Resources, Writing – review & editing **M. Williams**: Conceptualization, Methodology, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data and materials availability

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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