S1 Literature search methodology and results

**Literature search**

A search was conducted in October 2018 using the following Boolean string: (weed\* AND ("cover crop\*" OR "green manure" OR "catch crop\*") AND ("corn" OR "maize" OR "soybean\*")). This resulted in a total of 676 studies that were screened for eligibility based on the following three criteria:

(1) Studies must have been conducted in a US ‘Corn Belt’ state, defined as a state in the contiguous Midwestern region with the largest acreages of maize acres harvested in the most recent five years of available data (US Department of Agriculture National Agricultural Statistics Service) including: Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin

(2) Studies must have measured weed biomass and/or weed density

(3) Studies must have included a treatment that tested the effects of a fall-planted cover-crop (CC) followed by either maize or soybean against a treatment that included no CC holding all other factors constant. From this search, we screened the full text of 220 articles for inclusion in the database. From this, 15 articles met our three criteria (**Fig. S1.1**).

|  |
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|  |
| ***Figure S1.1.*** *PRISMA diagram* (Moher et al. 2009)for the literature search |

The 15 publications included in the database are listed below in alphabetical order:

1. Bernstein ER, Posner JL, Stoltenberg DE, Hedtcke JL (2011) Organically managed no-tillage rye-soybean systems: Agronomic, economic, and environmental assessment. Agron J 103:1169–1179. doi: 10.2134/agronj2010.0498
2. Cornelius CD, Bradley KW (2017) Influence of Various Cover Crop Species on Winter and Summer Annual Weed Emergence in Soybean. Weed Technol 31:503–513. doi: 10.1017/wet.2017.23
3. Crawford LE, Williams MM, Wortman SE (2018) An early-killed rye (Secale cereale) cover crop has potential for weed management in edamame (Glycine max). Weed Sci 66:502–507. doi: 10.1017/wsc.2018.5
4. Currie RS, Klocke NL (2005) Impact of a terminated wheat cover crop in irrigated corn on atrazine rates and water use efficiency. Weed Sci 53:709–716. doi: 10.1614/ws04-170r1.1
5. Davis AS (2010) Cover-Crop Roller–Crimper Contributes to Weed Management in No-Till Soybean. Weed Sci 58:300–309. doi: 10.1614/ws-d-09-00040.1
6. De Bruin JL, Porter PM, Jordan NR (2005) Use of a rye cover crop following corn in rotation with soybean in the upper Midwest. Agron J 97:587–598. doi: 10.2134/agronj2005.0587
7. Delate K, Cwach D, Chase C (2012) Organic no-tillage system effects on soybean, corn and irrigated tomato production and economic performance in Iowa, USA. Renew Agric Food Syst 27:49–59. doi: 10.1017/S1742170511000524
8. Fisk JW, Hesterman OB, Shrestha A, et al (2001) Weed suppression by annual legume cover crops in no-tillage corn. Agron J 93:319–325. doi: 10.2134/agronj2001.932319x
9. Forcella F (2014) Short- and full-season soybean in stale seedbeds versus rolled-crimped winter rye mulch. Renew Agric Food Syst 29:92–99. doi: 10.1017/S1742170512000373
10. Gallagher RS, Cardina J, Loux M (2003) Integration of cover crops with postemergence herbicides in no-till corn and soybean. Weed Sci 51:995–1001. doi: 10.1614/p2002-062
11. Gieske MF, Wyse DL, Durgan BR (2016) Spring- and Fall-Seeded Radish Cover-Crop Effects on Weed Management in Corn. Weed Technol 30:559–572. doi: 10.1614/wt-d-15-00023.1
12. Hoffman ML, Regnier EE, Cardina J (1993) Weed and corn (Zea mays) responses to a hairy vetch (Vicia villosa) cover crop. Weed Technol 7: 594-599. Doi:10.1017/S0890037X00037398
13. Mock VA, Creech JE, Ferris VR, et al (2012) Influence of Winter Annual Weed Management and Crop Rotation on Soybean Cyst Nematode ( Heterodera glycines ) and Winter Annual Weeds: Years Four and Five . Weed Sci 60:634–640. doi: 10.1614/ws-d-11-00192.1
14. Werle R, Burr C, Blanco-Canqui H (2017) Cereal rye cover crop suppresses winter annual weeds. Can J Plant Sci 98:498–500. doi: 10.1139/CJPS-2017-0267
15. Williams MM, Mortensen DA, Doran JW (1998) Assessment of weed and crop fitness in cover crop residues for integrated weed management. Weed Sci 46:595–603. doi: 10.1017/s0043174500091153

Data were recorded as reported (each site-year separately or averaged). No zero values were reported. When available, we sought to extract ancillary information (**Table S1.1**) from each study to accompany each paired observation.

***Table S1.1*** *Summary of factors recorded in database accompanying weed responses to cover cropping.*

|  |  |
| --- | --- |
| **Category** | **Variable** |
| *Management* | System tillage; time between cover-crop termination and cash crop planting; cover crop species, planting date, planting method, planting density, termination date, termination method, biomass at termination, subsequent crop; cash crop planting date, yield |
| *Environment* | State, latitude, longitude, soil type, organic matter content, aridity index\* |
| *Experiment* | Publication year, number of replicates, type of weed(s) measured, duration of experiment, timing of weed measurement with respect to crop planting, season of weed measurement\*\* |

\*an integrated measure of temperature, precipitation and potential evapotranspiration were derived from location coordinates using the CGIAR-CSI Global-Aridity and Global-PET databases (Zomer et al. 2008)

\*\* Spring: January-June; Summer: June-September; Fall : September – December

Over 95% of comparisons were done in treatments imposed the same or previous calendar year; we were therefore unable to include the duration of the experiment as an explanatory variable. The subsequent cash-crop’s planting density can affect a CC’s weed suppression effectiveness (Ryan et al. 2011), but that was also not included due to paucity of such data reporting. One comparison resulted in an extremely low LRR due to a CC treatment weed biomass of 1 g m-2 (SE = 1 g m-2) corresponding to a 99.9% reduction in weed biomass (Forcella 2013). This comparison was found to disproportionately influence results of the statistical models, and was therefore adjusted to equal the next highest reduction (97%) in weed biomass observed in the database.

**Database description**

These 15 published studies done in one of the 12 Midwest states measured weed biomass or weed density in a winter cover-cropped and no-cover treatment of maize or soybean (**Fig. S1.2**)

|  |
| --- |
| A close up of a map  Description automatically generated |
| ***Figure S1.2*** *The 12 contiguous US states with the highest maize production with published studies concerning cover-cropping effects on weed biomass and density; point shape indicates the weed response reported, point size the number of comparisons extracted from the study location, and point color the tillage classification of the study. No studies from North and South Dakota met our selection criteria.* |

The studies represented a range of management, environmental, and experimental contexts representative of the region (**Table S1.2**).

***Table S1.2*** *Management, environment, and experimental characteristics were extracted from each publication; weed biomass and weed density responses were separated into two datasets.*

|  |  |  |  |
| --- | --- | --- | --- |
| **Category** | **Factor** | **Biomass (n = 123)** | **Density (n = 119)** |
| ***Management*** | | | |
| System | Tillage | Tilled (n=30)  Zero-till (n=93) | Tilled (n=31)  Zero-till (n=88) |
|  | Time between cover crop termination and cash crop planting | -31 – 29 days | -31 – 13 days |
| Cover Crop | Type | Grass (n=46)  Non-grass (n=77)  *Non-grass category includes brassicas (3), legumes (74)* | Grass (n=31)  Non-grass (n=88)  *Non-grass category includes brassicas (9), legumes (73), mixtures (6)* |
|  | Planting date | Aug 15 – Oct 18 | Aug 15 – Oct 31 |
|  | Planting density | 13.4 – 180 kg seed ha-1 | 9 – 135 kg seed ha-1 |
|  | Termination date | April 18 – June 18 | April 18 – June 18 |
|  | Termination method | Several methods (n = 3)  herbicides (n = 54)  mechanical (roller crimper, mowing; n = 29)  winterkill (n = 37) | Several methods (n = 3)  herbicides (n = 53)  mechanical (roller crimper, mowing; n = 22)  winterkill (n = 37)  none (n = 4) |
|  | Cover crop biomass at termination | 130 – 9003 kg ha-1 | 0 – 9003 kg ha-1 |
| Cash crop | Subsequent crop | Maize (n=78)  Soybean (n=45) | Maize (n=73)  Soybean (n=42)  Averaged over maize and soybean phases† (n=4) |
|  | Cash crop planting date | April 20 – June 30 | April 27 – June 18 |
|  | Corn yield | 40-13500 kg ha-1 | 40-11200 kg ha-1 |
|  | Soybean yield | 300-3618 | 300-3310 kg ha-1 |
| ***Environment*** | | | |
|  | State | Illinois (17)  Kansas (9)  Michigan (44)  Minnesota (12)  Nebraska (11)  Ohio (25)  Wisconsin (5) | Iowa (4)  Illinois (5)  Indiana (4)  Michigan (45)  Minnesota (16)  Missouri (18)  Nebraska (6)  Ohio (21) |
|  | Latitude | 38.0 - 45.7N | 38.7 - 45.7N |
|  | Longitude | 81.9 – 101W | 83.0 – 101W |
|  | Soil type | Loam (n = 46)  Sandy loam (n = 1)  Silt Loam (n = 67)  Silty Clay Loam (n = 9) | Loam (n = 59)  Silt Loam (n = 61)  Silty Clay Loam (n = 9) |
|  | Organic matter content | 1.5 - 4.15% | 1 – 3.4% |
|  | Aridity index\* | 0.37 – 0.94 | 0.44 – 0.96 |
|  | Publication year | 1993 - 2018 | 1993 - 2018 |
| ***Experiment*** | | | |
| Design | Number of replicates | 3 - 5 | 3 – 6 |
|  | Type of weed(s) measured | Summer annual (86)  Winter annual (17)  Perennial (15)  Unknown (5) | Summer annual (75)  Winter annual (29)  Perennial (15) |
|  | Duration of experiment | 1-3 years (n=123)  4-5 years (n=0) | 1-3 years (n=115)  4-5 years (n=4) |
| Timing | Timing of weed measurement with respect to cash crop planting | Before (38)  After (119) | Before (38)  After (119) |
|  | Season of weed measurement\*\* | Spring (January-June; n = 19)  Summer (June-September; n = 104)  Fall‡ (October – December; n = 4) | Spring (n = 36)  Summer (n = 79) |
| †The study (Mock et al. 2012) reported weed densities averaged over both phases, but did not report crop yields  ‡This category was removed from analyses testing the significance of this modifier due to the small number of points representing the category  \*an integrated measure of temperature, precipitation and potential evapotranspiration were derived from location coordinates using the CGIAR-CSI Global-Aridity and Global-PET databases (Zomer et al. 2008).  \*\* Spring: January-June; Summer: June-September; Fall : September – December | | | |

**S2 Fitting statistical models**

Note that all R code for statistical analyses is available in the github repository **XXX**. The response (y) variable in all statistical analyses was the response ratio, defined as the value of the response in the CC treatment divided by the value in the no-cover treatment (Gurevitch et al. 2018). The ratios exhibited a log-normal distribution and were therefore log-transformed (log-response-ratio, LRR) for all statistical analyses. Values were back-transformed and presented as a percent change for interpretation purposes and reported as geometric means. To estimate over-all effect sizes, we fit a linear mixed-model using the lmer4 package (Bates et al. 2015) using the LRR as the response variable and a random intercept for each study with non-parametric weighting based on sample sizes (Adams et al. 1997) because only three of the 15 studies reported variances on weed measurements. Results were analyzed using the lmerTest (Kuznetsova et al. 2017) and emmeans (Lenth et al. 2018) packages.

For all linear mixed models subsequently described, a random intercept for each study and non-parametric weighting was used. Cover crop biomass is known to have a strong effect on weed suppression (Mirsky et al. 2013; Wallace et al. 2018; Baraibar et al. 2018). To assess an individual modifiers’ effect on weed responses, we first assessed whether the CC biomass produced at each modifier level was significantly different by fitting a mixed linear model with CC biomass as the response and an individual modifier as a predictor. Because these analyses showed CC type (grass and non-grass) significantly affected CC biomass production (p=0.01), we included CC biomass as a covariate when testing for the effect of CC type on weed suppression to control for these differences. This was done by including CC type (grass and non-grass), CC biomass at termination, and their interaction as fixed effects (plus the random intercept for study as previously described). The interaction was not significant based on nested model comparison, so the interaction was not included in the final model. For all other modifiers, they were assessed individually using a linear mixed model as described above with only one fixed effect modifier included at a time.

Significance was assigned at a p-value <0.05, but intermediate p-values (0.05-0.10) and effect sizes were investigated (Ho et al. 2019). The robustness of our results was assessed by removing one study at a time from the dataset and fitting the statistical model for each dataset individually (Philibert et al. 2012). Additionally, select individual points were assessed for disproportionately influencing results in the same manner. For significant results, robustness against possibly un-published non-significant results was assessed using a fail-safe number (Rosenthal 1979).

In the weed biomass (WBIO) database, the CC type significantly affected the amount of CC biomass (CCBIO) produced (p = 0.01), with grass CCs producing an estimated 3.95 Mg ha-1 of biomass, compared to 2.56 Mg ha-1 in non-grass. Therefore, CCBIO was used as a covariate in the statistical model testing for differences in CC type.

To estimate the amount of grass CCBIO needed at termination to achieve a 75% reduction in weed biomass, we fit a linear mixed model with CC type and CCBIO at termination as predictors (with study as a random intercept). The unconditioned fitted parameters were used to back-calculate the grass CC biomass at a CC-induced 75% reduction in weed biomass. The uncertainty around this value was estimated using the delta method (Ver Hoef 2012). Each point was categorized based on cash-crop yield and weed pressure responses; if the comparison exhibited both an increase in cash-crop yield and a decrease in weed pressure it was assigned ‘win-win’, otherwise it was assigned a value of ‘other’. To explore possible predictor combinations for win-win scenarios, we fit random forest models (Kuhn and Johnson 2013) using several R packages (Hothorn et al. 2006).

**S3 Results from statistical model-fitting**

*Overall model fits*

There was no evidence CCs reduced weed density (p=0.98; **Table S3.1**), but the sensitivity analysis identified one study (Gieske et al. 2016) using a radish (*Raphanus sativus*) CC whose removal drastically lowered the non-significance of the p-value (lowered from 0.98 to 0.26).

***Table S3.1*** *Overall model results with leave-one-study-out sensitivities*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Weed Response** | **p-value** | **Estimate** | **Lower 95% CI Bound** | **Upper 95% CI Bound** | **Study Left Out** |
| Density | 0.98 | 0.01 | -0.72 | 0.74 | NA |
| 0.95 | -0.02 | -0.86 | 0.82 | 3 |
| 0.83 | 0.08 | -0.73 | 0.88 | 4 |
| 0.76 | 0.1 | -0.66 | 0.87 | 5 |
| 0.81 | -0.09 | -0.88 | 0.71 | 6 |
| 0.94 | -0.03 | -0.85 | 0.8 | 8 |
| 0.93 | 0.03 | -0.8 | 0.86 | 9 |
| 0.26 | -0.19 | -0.68 | 0.3 | 10 |
| 0.64 | 0.14 | -0.54 | 0.83 | 11 |
| 0.93 | 0.03 | -0.79 | 0.85 | 12 |
| 0.91 | 0.04 | -0.78 | 0.86 | 13 |
| 0.97 | -0.01 | -0.84 | 0.81 | 15 |
| Biomass | 0.02 | -0.72 | -1.27 | -0.17 | NA |
| 0.03 | -0.76 | -1.39 | -0.12 | 1 |
| 0.04 | -0.65 | -1.25 | -0.04 | 2 |
| 0.01 | -0.82 | -1.39 | -0.25 | 3 |
| 0.03 | -0.73 | -1.36 | -0.1 | 4 |
| 0.03 | -0.66 | -1.23 | -0.08 | 5 |
| 0.01 | -0.8 | -1.37 | -0.23 | 7 |
| 0.02 | -0.81 | -1.44 | -0.18 | 9 |
| 0.02 | -0.59 | -1.06 | -0.11 | 11 |
| 0.04 | -0.67 | -1.28 | -0.06 | 12 |
| 0.02 | -0.79 | -1.4 | -0.19 | 14 |
| 0.04 | -0.66 | -1.28 | -0.05 | 15 |

***Table S3.2*** *Overall model results for models assessing differences in cash crop yields under cover-cropping versus no-cover treatments*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Database** | **p-value** | **Estimate** | **Lower 95% CI Bound** | **Upper 95% CI Bound** |
| Weed Biomass | 0.147 | -0.461 | -1.329 | 0.406 |
| Weed Density | 0.117 | -0.262 | -0.607 | 0.084 |

***Table S3.2*** *Weed biomass categorical modifier level contrasts*

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Modifier** | **Level 1** | **Level 2** | **Estimate** | **Standard Error** | **Degrees of Freedom** | **Statistic** | **p-value** |
| msmt\_season | spring | summer | -0.75 | 0.26 | 395.41 | -2.82 | 0.01 |
| msmt\_planting | after | before | 0.75 | 0.26 | 395.41 | 2.82 | 0.01 |
| weed\_group | perennial | winter annual | 1.03 | 0.33 | 432.46 | 3.14 | 0.01 |
| cc\_type2 | grass | non-grass | 0.44 | 0.17 | 80.66 | 2.50 | 0.01 |
| cropsys\_tillage | N | Y | 0.82 | 0.51 | 13.52 | 1.61 | 0.13 |
| weed\_group | perennial | summer annual | 0.60 | 0.33 | 379.78 | 1.81 | 0.17 |
| ccterm\_meth | H | M | 0.52 | 0.31 | 194.51 | 1.67 | 0.34 |
| weed\_group | summer annual | winter annual | 0.43 | 0.32 | 324.47 | 1.35 | 0.37 |
| crop\_follow | corn | soybean | 0.38 | 0.47 | 16.53 | 0.82 | 0.42 |
| cc\_type2 | grass | non-grass | 0.11 | 0.14 | 24.96 | 0.81 | 0.43 |
| ccterm\_meth | M | W | -0.64 | 0.45 | 160.63 | -1.42 | 0.49 |
| ccterm\_meth | D | W | -0.88 | 0.70 | 393.73 | -1.25 | 0.59 |
| ccterm\_meth | D | H | -0.76 | 0.62 | 443.61 | -1.23 | 0.61 |
| ccterm\_meth | H | W | -0.12 | 0.33 | 273.22 | -0.35 | 0.99 |
| ccterm\_meth | D | M | -0.24 | 0.69 | 369.01 | -0.35 | 0.99 |

***Table S3.3*** *Weed density categorical modifier level contrasts*

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Modifier** | **Level 1** | **Level 2** | **Estimate** | **Standard Error** | **Degrees of Freedom** | **Statistic** | **p-value** |
| msmt\_planting | after | before | 0.39 | 0.26 | 336.64 | 1.49 | 0.14 |
| weed\_group | perennial | winter annual | 0.52 | 0.29 | 435.50 | 1.77 | 0.18 |
| msmt\_season | spring | summer | -0.40 | 0.22 | 79.59 | -1.77 | 0.19 |
| weed\_group | summer annual | winter annual | 0.25 | 0.24 | 420.34 | 1.02 | 0.56 |
| weed\_group | perennial | summer annual | 0.28 | 0.29 | 439.41 | 0.94 | 0.61 |
| crop\_follow | corn | soybean | 0.08 | 0.36 | 10.28 | 0.24 | 0.97 |
| ccterm\_meth | D | H | -0.31 | 0.60 | 435.98 | -0.52 | 0.99 |
| ccterm\_meth | D | none | -0.60 | 1.35 | 18.43 | -0.45 | 0.99 |
| ccterm\_meth | D | M | -0.31 | 0.72 | 358.66 | -0.43 | 0.99 |
| ccterm\_meth | H | W | 0.11 | 0.31 | 399.01 | 0.34 | 1.00 |
| ccterm\_meth | none | W | 0.40 | 1.25 | 13.53 | 0.32 | 1.00 |
| ccterm\_meth | D | W | -0.21 | 0.67 | 428.18 | -0.31 | 1.00 |
| ccterm\_meth | H | none | -0.29 | 1.22 | 12.51 | -0.24 | 1.00 |
| ccterm\_meth | M | none | -0.30 | 1.25 | 13.59 | -0.24 | 1.00 |
| ccterm\_meth | M | W | 0.10 | 0.51 | 213.45 | 0.20 | 1.00 |
| ccterm\_meth | H | M | 0.00 | 0.41 | 185.11 | 0.01 | 1.00 |

***Table S3.4*** *Continuous modifier regression results*

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|  |
| ***Figure S3.1*** *A 75% reduction in weed biomass required 5 Mg ha-1 of grass cover crop biomass at termination.* |

S4. Supplementary Information on SALUS simple model calibration

# Systems Approach to Land-Use Sustainability (SALUS) model overview

SALUS (Basso and Ritchie 2015) is a cropping systems simulation platform that allows estimating the impact of diverse agricultural management strategies on various processes within the soil–plant–atmosphere continuum. The platform contains a suite of interconnected processed-based models derived from the well-validated CERES (Crop Estimation through Resource and Environment Synthesis) model, providing simulation of crop growth and development, and carbon, water, nitrogen, and phosphorus cycling dynamics on a daily time step. The model uses as input daily values of incoming solar radiation (MJ m−2), maximum and minimum air temperature (°C), and rainfall (mm), as well as information on soil characteristics and management. SALUS has been tested extensively for its ability to simulate various soil-crop processes including: soil carbon dynamics (Senthilkumar et al. 2009; Basso et al. 2018), crop yield (Basso et al. 2007), plant N uptake and phenology (Basso et al. 2010, 2011; Albarenque et al. 2016), nitrate leaching (Giola et al. 2012; Syswerda et al. 2012; Basso et al. 2016), water use efficiency (Ritchie and Basso 2008) and transpiration efficiency (Basso and Ritchie 2012). A general description on SALUS is provided by Basso and Ritchie (2015).

In SALUS, crop growth can be simulated following a *complex* or a *simple* modeling approach. In this study, we used the simple modeling approach. The *simple* crop model (SALUS-Simple henceforth) represents a ‘generic’ crop model with 20-25 predefined crop parameters, which can be easily adapted to characterize growth of many annual crops. SALUS-Simple follows the same approach used by ALMANAC (Agricultural Land Management Alternatives with Numerical Assessment Criteria, Kiniry et al., 1992). Briefly, the model uses crop parameters to calculate potential leaf area index (LAI) and radiation use efficiency (RUE) curves as function of thermal time, which in turn are used to estimate daily crop resource acquisition and potential crop growth. When run with water and nutrient limitations, the model calculates water and nutrient stress factors based on a daily supply-demand balance, which then are applied to reduce the rate of potential biomass growth. For a detailed description of the SALUS-Simple crop model, we refer the reader to Dzotsi et al. (2013).

# Data sources and model set up

We assembled a dataset of published literature studies conducted within the Corn Belt to set up and calibrate the SALUS-simple model. All of these studies reported measurements of winter rye cover crop biomass at termination, as well as cover crop planting and termination dates. This dataset contains observations from 12 studies, 6 of which also were included in our original meta-analysis dataset and the rest were available from a literature search from a previous study (Martinez-Feria et al. 2016). In total, the dataset included observations from 15 sites, amounting to 52 site-year combinations (Figure S2.1). We used 60% of the data for model training and 40% for model testing. The assembled dataset is shown in Table S2.1.

|  |  |
| --- | --- |
|  | ***Figure S2.1.*** *Geographical location of the experiments used for model calibration.* |

For each of the 15 sites, we retrieved daily weather data from the North American Land Data Assimilation System project phase 2 (NLDAS-2) dataset (Xia et al. 2012) using the single-pixel (0.125° resolution) extraction tool and formatter for SALUS (<https://salusmodel.ees.msu.edu/NLDAS/>). Soil information for each site was retrieved from the Soil SURvey GeOgraphic database (SSURGO; Soil Survey Staff), from which we selected data for the predominant soil series (map unit key) at each location.

Simulation for each experiment were run independently, from Jan-1 to June-30 of the following year, meaning that each simulation comprised a period of 18 months. We assumed both water- and N-limited rye cover crop growth. To provide for realistic initial conditions for soil water at cover crop planting, we simulated a maize crop, prior to cover crop planting. In the model, maize was planted in early May, fertilized with 150 kg N ha-1 at planting and harvested 10 days before the prescribed cover crop planting date. Planting density for rye cover crop was assumed at 300 plants m-2, 1.0 cm depth and 20 cm row spacing. No fertilizer was applied to rye in the model.

***Table S2.1.*** *Dataset of published estimates of rye cover crop biomass at terminations which was used for model training and testing*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Obs. ID** | **Used for** | **Source** | **Location** | **Planting** | **Termination** | **Biomass** |
| **(Mg ha-1)** |
| 1 | Training | Cornelius and Bradley, 2017 | Columbia, MO | 2012-9-11 | 2013-4-25 | 2.89 |
| 2 | 2013-9-12 | 2014-5-2 | 2.19 |
| 3 | 2014-9-10 | 2015-4-23 | 1.15 |
| 4 | Moberly, MO | 2013-9-12 | 2014-5-2 | 1.39 |
| 5 | 2014-9-10 | 2015-4-23 | 3.93 |
| 6 | Davis, 2010 | Urbana, IL | 2004-10-1 | 2005-5-13 | 7.10 |
| 7 | 2005-10-1 | 2006-5-12 | 6.00 |
| 8 | 2006-10-1 | 2007-5-11 | 6.00 |
| 9 | Bruin et al., 2005 | Rosemont, MN | 2001-10-25 | 2002-5-1 | 0.49 |
| 10 | 2001-10-25 | 2002-5-8 | 0.73 |
| 11 | 2001-10-25 | 2002-5-15 | 1.03 |
| 12 | 2001-10-25 | 2002-5-22 | 1.80 |
| 13 | 2002-11-1 | 2003-5-13 | 0.15 |
| 14 | 2002-11-1 | 2003-5-23 | 0.41 |
| 15 | 2002-11-1 | 2003-6-2 | 1.42 |
| 16 | 2002-11-1 | 2003-6-17 | 2.93 |
| 17 | Waseca, MN | 2001-10-18 | 2002-5-1 | 0.38 |
| 18 | 2001-10-18 | 2002-5-8 | 0.85 |
| 19 | 2001-10-18 | 2002-5-20 | 2.19 |
| 20 | 2001-10-18 | 2002-5-28 | 3.77 |
| 21 | 2002-10-11 | 2003-5-1 | 0.15 |
| 22 | 2002-10-11 | 2003-5-7 | 0.22 |
| 23 | 2002-10-11 | 2003-5-14 | 0.52 |
| 24 | 2002-10-11 | 2003-5-20 | 0.99 |
| 25 | Feyereisen et al., 2006 | St. Paul, MN | 2000-9-18 | 2001-5-25 | 5.90 |
| 26 | Forcella, 2014 | Stevens county, MN | 2009-9-2 | 2010-6-9 | 6.00 |
| 27 | 2010-9-20 | 2011-6-14 | 6.00 |
| 28 | Kaspar et al., 2007 | Ames, IA | 2001-9-20 | 2002-4-17 | 2.43 |
| 29 | 2002-9-10 | 2003-5-6 | 2.50 |
| 30 | 2003-10-2 | 2004-4-16 | 1.48 |
| 31 | 2004-10-6 | 2005-4-25 | 2.74 |
| 32 | Testing | Kaspar et al., 2012 | Ames, IA | 2005-9-30 | 2006-4-21 | 2.44 |
| 33 | 2006-10-24 | 2007-5-10 | 0.61 |
| 34 | 2007-9-28 | 2008-4-29 | 1.26 |
| 35 | 2008-10-29 | 2009-5-21 | 0.50 |
| 36 | 2009-9-28 | 2010-4-19 | 1.73 |
| 37 | Martinez-Feria et al., 2016 | Kelley, IA | 2008-10-21 | 2009-5-6 | 0.37 |
| 38 | 2009-11-6 | 2010-5-5 | 1.18 |
| 39 | 2010-10-4 | 2011-5-10 | 1.53 |
| 40 | 2011-10-10 | 2012-4-18 | 2.50 |
| 41 | 2012-10-15 | 2013-5-11 | 0.50 |
| 42 | Ruffo and Bollero, 2003 | Brownstown, IL | 1998-10-3 | 1999-4-28 | 4.73 |
| 43 | 1999-10-2 | 2000-4-29 | 2.92 |
| 44 | Urbana, IL | 1998-10-1 | 1999-5-2 | 4.02 |
| 45 | 1999-10-5 | 2000-5-4 | 3.16 |
| 46 | Strock et al., 2004 | Lamberton, MN | 1998-10-1 | 1999-4-30 | 2.70 |
| 47 | 1999-9-29 | 2000-4-11 | 1.00 |
| 48 | 2000-10-4 | 2001-5-16 | 0.50 |
| 49 | Werle et al., 2018 | North Platte, NE | 2016-9-20 | 2017-4-18 | 4.08 |
| 50 | 2016-10-17 | 2017-4-18 | 3.77 |
| 51 | Williams et al., 1998 | Ithaca, NE | 1994-9-20 | 1995-6-6 | 6.31 |
| 52 | 1995-9-20 | 1996-5-23 | 2.89 |

# Model calibration and performance

To calibrate the SALUS-simple model for simulating rye cover crop biomass, we first compared simulated values to data from the testing dataset (Table S2.1). To quantify model fit to the observed data we computed the Nash-Sutcliffe model efficiency (NSE) and root-mean-squared error (RMSE). The RMSE is a measure of model error (the closer to zero, the better), while NSE is a measure of model precision compared to an arithmetic mean (a value of 1 indicates perfect fit). The equation for these two measures can be seen in Archontoulis and Miguez (2013). Model fit was also evaluated visually by means of plotting the observed vs. simulated values, with the regression line as measure of model bias.

We used as a starting point the rye crop species parameters available in the ALMANAC model (Kiniry and Spanel, 2009; Table S2.2). Using this parameterization, however, the model tended to overestimate fall growth, which resulted in premature senescence in the spring. Therefore, we evaluated increasing the length of the growth cycle (TTtoMatr from 1200 to 1800 °C-day) and adjusting phenology (relTT\_P1, relTT\_Sn) and LAI curve parameters (relLAI\_P2). Additionally, because the model tended to overpredict biomass growth in the spring, we decreased maximum potential radiation use efficiency (RUEmax) from 3.0 to 2.0 g MJ (PAR)-1. A list of parameter values derived from the model training step are included in Table S2.2, and a model fit to the training data set is shown in Figures S2.2 and S2.3.

***Table S2.2.*** *Calibrated SALUS-simple parameters used to simulate winter rye cover crop growth.*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Parameter** | **Description** | **Units** | **Value** | |
| **ALMANAC (original)** | **Calibrated\*** |
| relTT\_P1 | Relative development thermal time at point 1 | °C-day °C-day-1 | 0.3 | 0.25 (0.05-0.45) |
| relLAI\_P1 | Relative LAI at point 1 | m2 m-2 | 0.01 | - |
| relTT\_P2 | Relative development thermal time at point 2 | °C-day °C-day-1 | 0.5 | - |
| relLAI\_P2 | Relative LAI at point 2 | m2 m-2 | 0.95 | 0.9 (0.9-0.99) |
| LAImax | Maximum leaf area index | m2 m-2 | 3 | - |
| RUEmax | Maximum potential radiation use efficiency | g MJ (PAR)-1 | 3 | 2 (1-3.5) |
| relTT\_Sn | Relative development thermal time at senescence | °C-day °C-day-1 | 0.8 | 0.5 (0.5-0.85) |
| SnParLAI | Parameter for RUE decline after senescence | unitless | 1 | - |
| SnParRUE | Parameter for RUE decline after senescence | unitless | 1 | - |
| TbaseDev | Base temperature for development | °C | 0 | - |
| ToptDev | Optimal temperature for development | °C | 15 | - |
| TTtoGerm | Development thermal time to germinate | °C-day | 20 | - |
| TTtoMatr | Development thermal time to mature | °C-day | 1200 | 1800 (1200-2500) |
| EmgInter | Intercept of emergence time calculation | leaf eq. | 15 | - |
| EmgSlope | Slope of emergence time calculation | leaf eq. cm-1 | 6 | - |
| HrvIndex | Harvest index | Mg Mg-1 | 0.42 | - |
| PlntN\_Em | Optimal N in plant at emergence | g g-1 | 0.0226 | - |
| PlntN\_Hf | Optimal N in plant halfway to maturity | g g-1 | 0.018 | - |
| PlntN\_Mt | Optimal N in plant at maturity | g g-1 | 0.014 | - |
| GrnN\_Mt | Optimal N in grain at maturity | g g-1 | 0.023 | - |
| CHeight | Approximate height of crop | m | 1.0 | - |
| \*Values within parenthesis show the range explored in the calibration | | | | |

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| --- |
|  |
| ***Figure S2.2.*** *Example of rye cover crop spring growth as simulated by the SALUS-simple crop model. The data for the experiments shown here were obtained from Bruin et al. (2005).* |

Having calibrated the SALUS-Simple crop model to simulate rye growth, the next step was to compare the simulated values to the independent measurement in the testing dataset. Considering that set-up and model training was largely based on limited (i.e. publicly available) data and literature values, the SALUS-simple model was able to satisfactorily reproduce the measured cover crop biomass at termination in the testing dataset. Biomass across all sites in the testing dataset were simulated with a RMSE of 1.2 Mg ha-1. This was about the same compared to the training dataset (1.1 Mg ha-1), which suggest no overfitting of the training data. The model did tend to overpredict the rye biomass in the testing dataset compared to the training, especially in the high yielding environments. This translated to lower NSE compared to the training data (0.74 vs. 0.39), although it was still within acceptable ranges. Based on these results we deemed this model calibration appropriate for estimating rye biomass growth as a function of weather, soils and management across the US Corn Belt.

|  |  |
| --- | --- |
|  | ***Figure S2.3.***  *SALUS simple model fit to the training and testing datasets. NSE = Nash-Sutcliffe model efficiency; RMSE = root mean squared error.* |

S3. Model fitting results

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