SALUS 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 S4.1**). We used 60% of the data for model training and 40% for model testing. The assembled dataset is shown in **Table S4.1**.

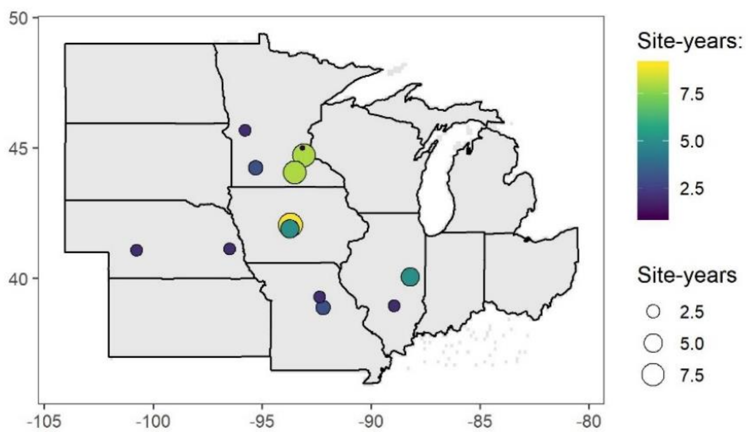

Figure S4.1. *Geographical location of the experiments used for model calibration.*

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 1-Jan to 30-June 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 S4.1. *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 S4.1). 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 S4.2, and a model fit to the training data set is shown in Figures S4.2 and S4.3.

Table S4.2. *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	m^2 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	m^2 m^{-2}	0.95	0.9 (0.9-0.99)
LAImax	Maximum leaf area index	m^2 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				

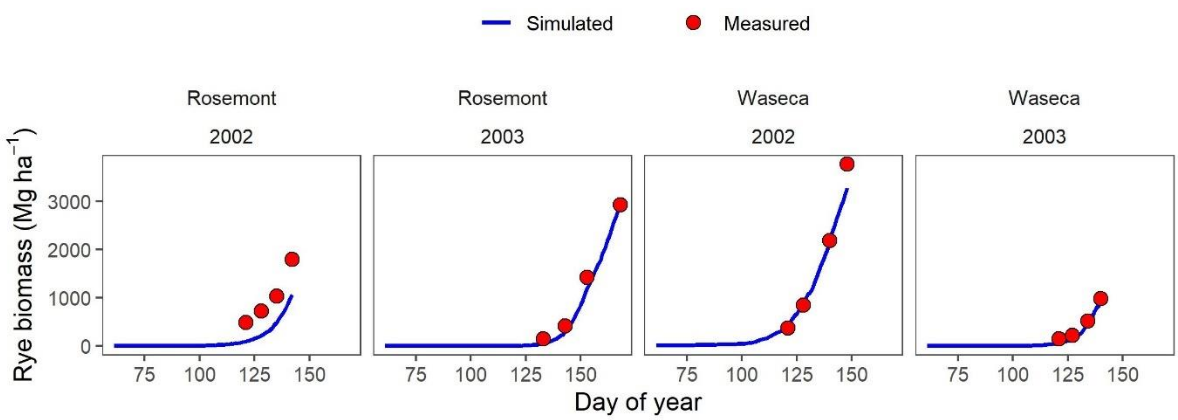

Figure S4.2. *Example of rye cover crop spring growth as simulated by the SALUS-simple crop model. The data for the experiments shown here were obtained from Bruin et al. (2005).*

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.

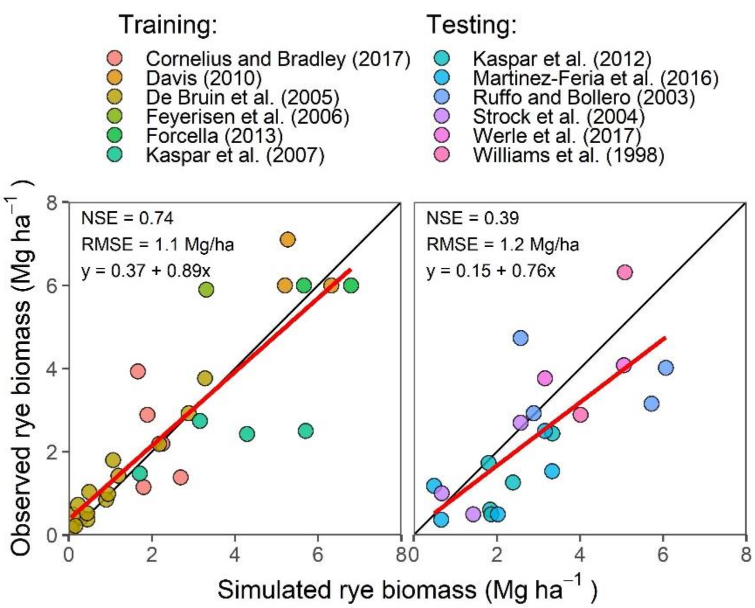

Figure S4.3. *SALUS simple model fit to the training and testing datasets. NSE = Nash-Sutcliffe model efficiency; RMSE = root mean squared error.*

Supplementary Material References

Adams, D.C., J. Gurevitch, and M.S. Rosenberg. 1997. Resampling Tests for Meta-Analysis of Ecological Data. REPORTS Ecol. 78(5): 1277–1283. http://www.public.iastate.edu/~dcadams/PDFPubs/1997-Adams_Gur_Ros-Ecol.pdf.

Albarenque, S.M., B. Basso, O.P. Caviglia, and R.J.M. Melchiori. 2016. Spatio-temporal nitrogen fertilizer response in maize: Field study and modeling approach. Agron. J. 108(5): 2110–2122. doi: 10.2134/agronj2016.02.0081.

Archontoulis, S. V, and F.E. Miguez. 2013. Supplemental Materials for Nonlinear for Nonlinear Regression Models and Applications in Agricultural Research. Agron. J. 13: 1–13. doi: 10.2134/agronj2012.0506.

Baraibar, B., D.A. Mortensen, M.C. Hunter, M.E. Barbercheck, J.P. Kaye, et al. 2018. Growing degree days and cover crop type explain weed biomass in winter cover crops. Agron. Sustain. Dev. 38(6): 1–9. doi: 10.1007/s13593-018-0543-1.

Basso, B., M. Bertocco, L. Sartori, and E.C. Martin. 2007. Analyzing the effects of climate variability on spatial pattern of yield in a maize-wheat-soybean rotation. Eur. J. Agron. doi: 10.1016/j.eja.2006.08.008.

Basso, B., D. Cammarano, A. Troccoli, D. Chen, and J.T. Ritchie. 2010. Long-term wheat response to nitrogen in a rainfed Mediterranean environment: Field data and simulation analysis. Eur. J. Agron. doi: 10.1016/j.eja.2010.04.004.

Basso, B., B. Dumont, B. Maestrini, I. Shcherbak, G.P. Robertson, et al. 2018. Soil Organic Carbon and Nitrogen Feedbacks on Crop Yields under Climate Change. Ael 3(1): 0. doi: 10.2134/ael2018.05.0026.

Basso, B., P. Giola, B. Dumont, M.D.A. Migliorati, D. Cammarano, et al. 2016. Tradeoffs between Maize Silage Yield and Nitrate Leaching in a Mediterranean Nitrate-Vulnerable Zone under Current and Projected Climate Scenarios. PLoS One 11(1): e0146360. doi: 10.1371/journal.pone.0146360.

Basso, B., and J.T. Ritchie. 2012. Assessing the impact of management strategies on water use efficiency using soil-plant-atmosphere models. Vadose Zo. J. doi: 10.2136/vzj2011.0173.

Basso, B., and J.T. Ritchie. 2015. Simulating Crop Growth and Biogeochemcial Fluxes in Response to Land Management Using the SALUS Model. The Ecology of Agricultural Landscapes: Lon-term Research on the Path to Sustainability. Oxford University Press, New York, NY USA. p. 252–274

Basso, B., J.T. Ritchie, D. Cammarano, and L. Sartori. 2011. A strategic and tactical management approach to select optimal N fertilizer rates for wheat in a spatially variable field. Eur. J. Agron. 35(4): 215–222. doi: 10.1016/J.EJA.2011.06.004.

De Bruin, J.L., P.M. Porter, and N.R. Jordan. 2005. Use of a rye cover crop following corn in rotation with soybean in the upper Midwest. Agron. J. 97(2): 587–598. doi: 10.2134/agronj2005.0587.

Cornelius, C.D., and K.W. Bradley. 2017. Carryover of Common Corn and Soybean Herbicides to Various Cover Crop Species. Weed Technol. 31(1): 21–31. doi: 10.1614/wt-d-16-00062.1.

Davis, A.S. 2010. Cover-Crop Roller–Crimper Contributes to Weed Management in No-Till Soybean.

Weed Sci. 58(3): 300–309. doi: 10.1614/ws-d-09-00040.1.

Dzotsi, K.A., B. Basso, and J.W. Jones. 2013. Development, uncertainty and sensitivity analysis of the simple SALUS crop model in DSSAT. Ecol. Modell. 260: 62–76. doi: 10.1016/j.ecolmodel.2013.03.017.

Feyereisen, G.W., B.N. Wilson, G.R. Sands, J.S. Strock, and P.M. Porter. 2006. Potential for a rye cover crop to reduce nitrate loss in southwestern Minnesota. Agron. J. 98(6): 1416–1426. doi: 10.2134/agronj2005.0134.

Forcella, F. 2014. Short- and full-season soybean in stale seedbeds versus rolled-crimped winter rye mulch. Renew. Agric. Food Syst. 29(1): 92–99. doi: 10.1017/S1742170512000373.

Giola, P., B. Basso, G. Pruneddu, F. Giunta, and J.W. Jones. 2012. Impact of manure and slurry applications on soil nitrate in a maize-triticale rotation: Field study and long term simulation analysis. Eur. J. Agron. doi: 10.1016/j.eja.2011.12.001.

Gurevitch, J., J. Koricheva, S. Nakagawa, and G. Stewart. 2018. Meta-analysis and the science of research synthesis. Nature 555(7695): 175–182. doi: 10.1038/nature25753.

Ho, J., T. Tumkaya, S. Aryal, H. Choi, and A. Claridge-Chang. 2019. Moving beyond P values: data analysis with estimation graphics. Nat. Methods 16(7): 565–566. doi: 10.1038/s41592-019-0470-3.

Ver Hoef, J.M. 2012. Who invented the delta method? Am. Stat. 66(2): 124–127. doi: 10.1080/00031305.2012.687494.

Hothorn, T., K. Hornik, A. Zeileis, K.H. and A.Z. Torsten Hothorn, T. Hothorn, et al. 2006. Unbiased recursive partitioning: A conditional inference framework. J. Comput. Graph. Stat. 15(3): 651–674. doi: 10.1198/106186006X133933.

Kaspar, T.C., D.B. Jaynes, T.B. Parkin, and T.B. Moorman. 2007. Rye cover crop and gamagrass strip effects on NO3 concentration and load in tile drainage. J. Environ. Qual. 36(5): 1503–1511. doi: 10.2134/jeq2006.0468.

Kaspar, T.C., D.B. Jaynes, T.B. Parkin, T.B. Moorman, and J.W. Singer. 2012. Effectiveness of oat and rye cover crops in reducing nitrate losses in drainage water. Agric. Water Manag. 110(3): 25–33. doi: 10.1016/j.agwat.2012.03.010.

Kiniry, J.R., and D.A. Spanel. 2009. ALMANAC User Guide and References: Manual for the Agricultural Land Management Alternatives with Numerical Assessment Criteria Model.

Kuhn, M., and K. Johnson. 2013. Applied predictive modeling. Vol. 26. Springer, New York.

Kuznetsova, A., P.B. Brockhoff, and R.H.B. Christensen. 2017. lmerTest Package: Tests in Linear Mixed Effects Models. J. Stat. Softw. 82(13). doi: 10.18637/jss.v082.i13.

Lenth, R., H. Singmann, and J. Love. 2018. Emmeans: Estimated maringal means, aka least-squares means.

Martinez-Feria, R.A., R. Dietzel, M. Liebman, M.J. Helmers, and S. V Archontoulis. 2016. Rye cover crop effects on maize: A system-level analysis. F. Crop. Res. 196: 145–159. doi: 10.1016/j.fcr.2016.06.016.

Mirsky, S.B., M.R. Ryan, J.R. Teasdale, W.S. Curran, C.S. Reberg-Horton, et al. 2013. Overcoming Weed Management Challenges in Cover Crop–Based Organic Rotational No-Till Soybean Production in the Eastern United States. Weed Technol. 27(1): 193–203. doi: 10.1614/wt-d-12-00078.1.

Moher, D., A. Liberati, J. Tetzlaff, D.G. Altman, D. Altman, et al. 2009. Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. Ann. Intern. Med. 151(4): 264–269. doi: 10.7326/0003-4819-151-4-200908180-00135.

Philibert, A., C. Loyce, and D. Makowski. 2012. Assessment of the quality of meta-analysis in agronomy. Agric. Ecosyst. Environ. 148: 72–82. doi: 10.1016/j.agee.2011.12.003.

Ritchie, J.T., and B. Basso. 2008. Water use efficiency is not constant when crop water supply is adequate or fixed: The role of agronomic management. Eur. J. Agron. 28(3): 273–281. doi: 10.1016/j.eja.2007.08.003.

Rosenthal, R. 1979. The file drawer problem and tolerance for null results. Psychol. Bull. 86(3): 638–641. doi: 10.1037/0033-2909.86.3.638.

Ruffo, M.L., and G.A. Bollero. 2003. Modeling rye and hairy vetch residue decomposition as a function of degree-days and decomposition-days. Agron. J. 95(4): 900–907. doi: 10.2134/agronj2003.9000.

Ryan, M.R., S.B. Mirsky, D.A. Mortensen, J.R. Teasdale, and W.S. Curran. 2011. Potential Synergistic Effects of Cereal Rye Biomass and Soybean Planting Density on Weed Suppression. Weed Sci. 59(2): 238–246. doi: 10.1614/ws-d-10-00110.1.

Senthilkumar, S., B. Basso, A.N. Kravchenko, and G.P. Robertson. 2009. Contemporary evidence of soil carbon loss in the U.S. corn belt. Soil Sci. Soc. Am. J. doi: 10.2136/sssaj2009.0044.

Soil Survey Staff. Soil Survey Geographic (SSURGO) Database.

Strock, S.J., P.M. Porter, and M.P. Russelle. 2004. Cover cropping to reduce nitrate loss through subsurface drainage in the northern U.S. corn belt. J. Environ. Qual. 33(3): 1010–1016. doi: 10.2134/jeq2004.1010.

Syswerda, S.P., B. Basso, S.K. Hamilton, J.B. Tausig, G.P. Robertson, et al. 2012. Long-term nitrate loss along an agricultural intensity gradient in the Upper Midwest USA. Ecosyst. Environ. 149: 10–19. doi: 10.1016/j.agee.2011.12.007.

Wallace, J.M., C.L. Keene, W. Curran, S. Mirsky, M.R. Ryan, et al. 2018. Integrated Weed Management Strategies in Cover Crop-based, Organic Rotational No-Till Corn and Soybean in the Mid-Atlantic Region. Weed Sci. 66(1): 94–108. doi: 10.1017/wsc.2017.53.

Werle, R., C. Burr, and H. Blanco-Canqui. 2018. Cereal rye cover crop suppresses winter annual weeds. Can. J. Plant Sci. 98: 498–500. doi: 10.1139/cjps-2017-0267.

Williams, M.M., D.A. Mortensen, and J.W. Doran. 1998. Assessment of weed and crop fitness in cover crop residues for integrated weed management. Weed Sci. 46(5): 595–603. doi: 10.1017/s0043174500091153.

Xia, Y., K. Mitchell, M. Ek, J. Sheffield, B. Cosgrove, et al. 2012. Continental-scale water and energy flux analysis and validation for the North American Land Data Assimilation System project phase 2 (NLDAS-2): 1. Intercomparison and application of model products. 117(D3): n/a-n/a. doi: 10.1029/2011JD016048.

Zomer, R.J., A. Trabucco, D.A. Bossio, and L. V. Verchot. 2008. Climate change mitigation: A spatial analysis of global land suitability for clean development mechanism afforestation and reforestation. Agric. Ecosyst. Environ. 126(1–2): 67–80. doi: 10.1016/j.agee.2008.01.014.