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Cover crops decrease maize yield variability in sloping landscapes through increased water during reproductive stages

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ABSTRACT

Rolling hill style topography is a common feature of agricultural land throughout the United States. Topographic complexity causes subfield variation in soil resources such as water and nutrients, leading to a mosaic of high- and low-productivity zones that can shift from one year to the next due to weather. Stabilizing yields across these productivity zones using agroecological methods may improve land use efficiency, prevent unnecessary cropland expansion, and reduce the environmental impact of these systems. Here, we hypothesized that cover crops may help to reduce soil water and nutrient losses and increase the stability of subsequent maize yields across time and space. We performed a field study to evaluate the effect of a cereal rye (*Secale Cereale* L.) cover crop on maize (*Zea mays* L.) yield at three landscape positions (summit, backslope, and toeslope) in Central KY in 2018–2019, and calibrated the DSSAT v4.7.0.001 computer simulation program to test our hypothesis across a thirty-year period. Our field trial showed pronounced variability in maize yield across different landscape positions, ranging from 6.3 Mg ha^{-1} in the backslope, to 12.2 Mg ha^{-1} in the toeslope. Model simulations were consistent with results from our field trial and indicated that low yields in the backslope were primarily due to water stress, with >10 % yield reductions in 17 out of 30 simulated years relative to simulations under irrigated conditions where water was not limiting. In contrast, the toeslope and summit positions experienced >10 % yield reductions due to water stress in only 6 of the 30 years. Growing a cereal rye cover crop before maize reduced the frequency of water stress and raised maize yields in the backslope by 6% (500 kg ha^{-1}) on average, and 24 % (1235 kg ha^{-1}) during dry years. The coefficient of variation across all weather conditions and landscape positions was reduced from 33 % to 26 % when maize followed a rye cover crop compared to fallow. The yield benefits of the cover crop were associated with decreased soil evaporation and runoff that increased water availability during anthesis and late maize reproductive phases. Crop model simulations allowed us to evaluate and parse out the fundamental drivers of the interaction between cover crops and complex topography under different weather scenarios. Overall, our study demonstrates the outsized potential of cover crops to increase and stabilize grain yields in rolling hill landscapes and emphasizes the value of cover crops as a tool for ecological intensification.

1. Introduction

Much of the rainfed crop production area of the United States is characterized by topographic variability. In complex terrain, downslope movement of fertile topsoil over time can decrease soil depth and fertility at upslope positions while increasing it in low-lying positions. In addition, low elevation landscape positions often have a water table closer to the soil surface, which slows decompositions and promotes soil organic matter accumulation. Variation in soil resources due to topographic effects can directly impact crop growth (Corre et al., 2002). Previous field-scale research has indicated that landscape position can explain up to 60 % of spatial yield variability (Jiang and Thelen, 2004). A recent satellite-based regional analysis of crop yields demonstrated that sub-field variability in soil characteristics and topography is often more important than management in explaining yield variability throughout the Central US (Lobell and Azzari, 2017).

The impact of topographic setting on crop yield varies from year to year in response to weather conditions (Kravchenko and Bullock, 2000; Kumhalova et al., 2011; Maestrini and Basso, 2018). The accumulation of water in depressional areas gives rise to relatively high productivity

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during low-rainfall years, but can also lead to reduced yields via delayed emergence, decreased root growth, and nutrient uptake during wet years (Wankert et al., 1981). Conversely, crops grown in summit and sloping positions can be highly productive during wet years but experience water stress much earlier than foot- and toeslope positions during dry years due to lower soil water storage capacity and downslope losses. For instance, a study of grain yield response to landscape position in shallow, claypan soils indicated maize yields were significantly lower in backslope position than in the summit and toeslope during select years of the study. Further, the coefficient of variation for maize yields over time was 10 percent higher in maize grown on the backslope, compared to the deeper toeslope positions (Yost et al., 2016). Analyses of large-scale spatial datasets of the Central US indicate that 28 % of active farmland, largely depressions and sloping uplands, can be classified as unstable, with yields varying by up to 33 % from year to year (Basso et al., 2019; Martinez-Feria and Basso, 2020).

Spatiotemporal crop yield variability poses economic and environmental challenges. Yield loss in unstable zones costs an estimated 535 M USD per year in lost production (Martinez-Feria and Basso, 2020). Additionally, low N use efficiency in heterogeneous cropland poses a risk to downstream ecosystem sustainability. When low yielding areas are fertilized at the same rate as high-yielding areas, fertilizer is at risk of not being taken up by plants and instead being transported downstream, causing harm to the environment (Basso et al., 2016; Vitousek et al., 2013). The instability in spatial yield patterns from one year to the next make it challenging to predict economically and environmentally optimum N fertilizer rates for different areas within the same field. From the Central US alone, annual fertilizer loss from unstable cropland costs 485 M USD, and adds 1.12 Tg of reactive N to the environment (Basso et al., 2019). The inefficiencies in nutrient cycling and water use that arise in areas of rolling cropland provide an opportunity to intensify agricultural production; if yields can be stabilized and nutrients conserved, these areas have potential to increase economic and environmental sustainability.

Ecological intensification aims to sustain or increase yields while reducing environmental impact by managing ecological processes (Bommarco et al., 2013). Cover crops may provide an avenue for ecological intensification of rolling cropland. By protecting topsoil against erosion, retaining soil nutrients, and creating a residue that conserves soil moisture (Kaye and Quemada, 2017), cover crops can reduce environmental impact while making cash crops less sensitive to topographic and weather variation. Working at the scale of a typical crop field, Munoz et al. (2014) found a cover crop was most beneficial for maize yield during dry years, and the positive effect was most pronounced in the summit and sloping positions of the landscape. Other multiple site-year studies have shown that cropping system diversification, which often includes cover crop integration, increases resilience to environmental stressors such as drought (Bowles et al., 2020; Gaudin et al., 2015). Thus, cover crops may offer a management option to sustain yields in the face of rising spatial yield heterogeneity (Lobell and Azzari, 2017) and weather variability (Wuebbles et al., 2017). However, because most assessments of resilience occur post-hoc, the specific causes of the rotation effect remain poorly defined (Bennett et al., 2012; Bowles et al., 2020). Moreover, most research has been conducted in relatively uniform research plots that may misrepresent cropping system effects at field scale (Kravchenko et al., 2017).

Evaluating the role of cover crops in ecological intensification of rolling cropland requires several site-years of data on the rotation sequence, which are difficult to generate with field research alone due to time and cost constraints. Further, variables beyond the researcher's control, especially factors driven by weather such as the rate of biogeochemical processes, drainage, and crop evapotranspiration can vary dramatically and have large consequences on the results of two- to three-year long field trials. Well calibrated agricultural system models allow researchers to evaluate different management options across a range of environmental conditions. Crop models calibrated with data from empirically based-studies can integrate processes and study complex system dynamics to reveal management adaptations for the sustainable use of water (Dietzel et al., 2016; Ruíz-Nogueira et al., 2001; Saseendran et al., 2015; Singh et al., 2017), N fertilizer (Puntel et al., 2016; Salmerón et al., 2014; Sela et al., 2017), improving soil quality under competing uses of water (Chatterjee et al., 2020; Adhikari et al., 2017; Basche et al., 2016a,b; Pinto et al., 2017), reducing environmental impact (Malone et al., 2017; Martinez-Feria et al., 2018, 2016a) and increasing climate resilience (Battisti and Sentelhas, 2017; Sentelhas et al., 2015). There has been some application of process-based crop models to study sub-field variation in soil resources and spatially connected processes in complex topography (Albarenque et al., 2016; Basso et al., 2011; Basso and Ritchie, 2015; McNunn et al., 2019). However, crop model applications that focus on cover crop management adaptations in rolling hill landscapes are still pending to our knowledge. Moreover, cover crop effects and optimal management recommendations are likely to be specific to edaphoclimatic conditions.

The goal of this study was to quantify the effect of a winter cover crop on maize yields and their variability over space and time, to evaluate the potential of this management adaptation in rolling hill terrain, and to inform future field experimental research and on-farm management decisions. We hypothesized that the addition of a cover crop would increase maize yields in particularly low-yielding settings by reducing crop water and N stress, thus reducing yield variability among landscape positions and among years. To test this hypothesis, we calibrated a cropping system model with data collected in 2019 in Lexington, KY from a winter fallow – maize system rotation with three landscape positions and different N fertilizer levels, and then conducted a simulation sensitivity analysis across 30 years (1989–2019) and two soil N fertility levels. By coupling field data and model simulations, we attempt to advance our knowledge of ecological intensification through cover crops in agroecosystems with complex terrain.

2. Materials and methods

2.1. Description of field trial

From October 2018 through October 2019, a field trial was conducted to investigate the interactive effects of topography, cover crop use, and N fertilizer rate on maize yield. The trial took place at the University of Kentucky North Farm (38.123 °N, -84.490 °W), near Lexington, KY USA. The field site was selected to represent a hillslope setting found in producers' fields in this region. The topographic positions were delineated based on their elevation and slope (Fig. 1). Soils at the summit position were classified as fine-silty, mixed, active, mesic Typic Paleudalfs (Bluegrass series). Soils at the backslope position were classified as fine, mixed, active, mesic Mollic Hapludalfs (McAfee series). Soils in the toeslope position were classified as fine-silty, mixed, active, mesic Fluventic Hapludolls (Huntington series) (National Cooperative Soil Survey, 2020). The soils are formed in residuum of phosphatic limestone, which varies in depth by landscape position (depth to bedrock of 20–45 cm on the backslope, 100 cm on the summit, and >100 cm on the toeslope). Average annual precipitation at the site is 1088 mm and average annual temperature is 13.1° C (1981–2010, http://weather.uky.edu/).

The field was in long term hay production prior to cultivation. In October 2018, the field was sprayed with glyphosate, moldboard plowed, and then disked to prepare the seedbed for the cover crop planting. Between April 2018 and April 2019, lime and potash were applied according to soil test results and University of Kentucky recommendations for optimum maize production. No other nutrients were considered suboptimal for maize growth according to the soil test.

The experimental plots were arranged in a split-split plot randomized complete block design, with three replications. The main plot factor was

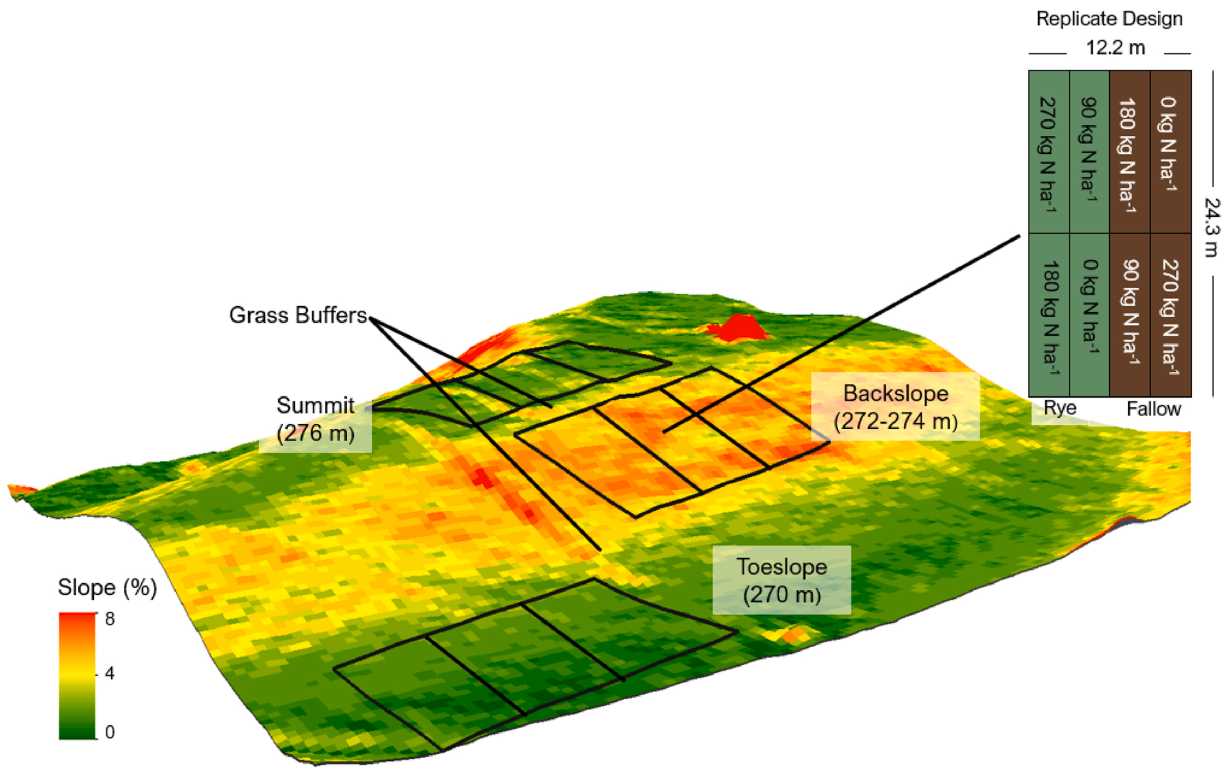

Fig. 1. Topographic map with % slope and experimental layout for field experiments in 2019.

landscape position (n = 3), the sub-plot factor was cover crop treatment (n = 2), and the sub-sub-plot factor was N rate (n = 4) (Fig. 1). A cereal rye cover crop was drill-seeded in the fall of 2018. Fallow plots were left bare throughout the winter, and weeds in these plots were not chemically controlled during cover crop growth. The cover crop was chemically terminated at the Feekes 7 growth stage (Knott, 2016), and left on the soil surface. Following cover crop termination, maize was no-till planted. Nitrogen fertilizer treatments consisted of four rates (0, 90, 180, and 270 kg N ha^{-1}), with 45 kg N ha^{-1} applied at planting in all treatments receiving N fertilizer, and the remainder applied at the V5 growth stage. Further details concerning field management activities can be found in Table 1.

Table 1
Summary of field operations for cover crop and maize management in 2019 field experiment.

Field Operation	Date	Management Details
Cover Crop Planting	10/12/2018	Cover crop was drill seeded into 19 cm rows with at a seeding rate of 70 kg ha^{-1}.
Cover crop termination	4/13/2019	Cover crop was chemically terminated with a combination of glyphosate and 2,4-D and left on the soil surface.
Maize planting	5/08/2019	Maize was no-till planted in 76 cm rows at a target population of 78,000 plants ha^{-1}. A 5 × 5 starter fertilizer was subsurface banded at 45 kg N ha^{-1} as 32% urea ammonium nitrate (UAN) in plots receiving N fertilizer.
Maize sidedress fertilization	6/04/2019	At the V5 stage, 32 % UAN was dribbled on the soil surface to supply the remainder of the full N fertilizer rate.
Maize R1 sampling	7/18/2019	Six maize plants from the center two rows were removed at R1 for biomass and nutrient content measurements.
Maize harvest	9/11/2019	Maize was hand harvested from a 6.1-m section of each plot for yield calculations, and 8 plants were removed from the center two rows for biomass and nutrient content measurements.

2.2. Experimental data collection and analysis

Two days prior to chemical termination of the cover crop, a random 0.25 m^2 aboveground biomass sample containing cereal rye and/or weeds was collected from each experimental unit (i.e., the sub-sub-plot level, n = 72). Maize biomass samples were collected at R1 (7/18/2019) by removing six plants from the center two rows in the plots receiving 0 kg N ha^{-1} and 270 kg N ha^{-1} (n = 36), and at R6 (9/11/2019), by removing eight plants from the center two rows of all plots (n = 72). All biomass samples were dried, weighed, ground, and analyzed for C and N concentrations via dry combustion. Maize biomass on an area basis was calculated based on the measured plant population from each plot. Maize grain yield was determined by hand harvesting ears from 6.1 m of the center two rows of each plot. Weight per ear, kernels per ear, and unit kernel weight were quantified from an eight-ear subsample. Maize populations were determined by counting plants in the hand-harvested area of each plot. Maize biomass on an area basis was calculated based on the measured plant population from each plot.

Volumetric soil water content was measured throughout the growing season using a Sentek Diviner 2000 Capacitance probe. Access tubes were installed in 270 kg N ha^{-1} treatment plots (n = 18). Volumetric water content was measured at 10 cm increments down to 100 cm or bedrock, depending on the soil profile depth. Each measurement was taken as the average from three readings per sampling.

Soil samples from each landscape position were collected to a depth of 60 cm at cover crop planting, to determine bulk density, texture, pH, cation exchange capacity, and soil organic C and N. Soil texture analysis was performed at the University of Kentucky Regulatory Services soil lab, using the micropipette method (Burt et al., 1993; Miller and Miller, 1987). Soil pH was measured using the Sikora Buffer method (Sikora, 2006). Cation exchange capacity was determined via ammonium saturation of exchange sites. Soil C and N concentrations were measured using a dry combustion analyzer. Soil samples were also collected to a depth of 60 cm at cover crop termination to establish inorganic N (Crutchfield and Grove, 2011) and soil water storage for model initialization.

Treatment effects on maize yield during our experimental trial were evaluated using Type III sums of squares ANOVA using lme4 in R (v1.1–23 Bates et al., 2015). In the linear mixed model, cover crop, landscape position, and N fertilizer rate and their interactions were considered fixed effects, and replicate, replicate x landscape position interaction, and replicate x landscape position x cover crop interaction were considered random effects. Cover crop biomass and N content were analyzed in a similar manner, except that cover crop and N fertilizer rate were not included as factors in the model. Total soil water storage (mm) in 0−0.5 and 0.5−1 m soil profile depths was analyzed using a repeated measures ANOVA using lme4 in R (v1.1–23, Bates et al., 2015). In the linear mixed model, total soil water storage was the response variable, cover crop and landscape position and their interaction were considered fixed effects, and sample date, replicate, and replicate x landscape position were random effects. To analyze the effect of the cover crop on soil water storage during key growth stages, soil water storage was averaged across dates during vegetative, anthesis, and reproductive growth periods. The data for each growth stage was then analyzed using a Type III sums of squares ANOVA using lme4 in R (v1.1–23, Bates et al., 2015), where cover crop, landscape position, and their interaction were considered fixed effects, and replicate and replicate x landscape position were considered random effects.

2.3. *Simulation of field study*

2.3.1. *Description of software used and model settings*

The Decision Support System for Agro-technology Transfer (DSSAT) v.4.7.1.001 is a suite of dynamic, process-based modeling tools to simulate the C, N, and water balance in cropping systems (Jones et al., 2003; Hoogenboom et al., 2019). The Sequence option was used to simulate the CERES-Wheat and CERES-Maize models in rotation, with carryover of water, C, and N between the wheat and maize phases. Reference evapotranspiration was simulated following the FAO-56 approach (Allen et al., 1998), and the Sulieman-Ritchie method was used to calculate soil evaporation (Ritchie et al., 2009). The Suleiman-Ritchie method was selected based on best fit of observed soil moisture in the top 0–10 cm soil layer in fallow treatments. Soil organic C and N turnover were simulated using the CENTURY-based option in DSSAT (Parton et al., 1988, 1994).

Simulations require management, weather, genotype, and soil input data. Management inputs were chosen to reflect the management of the field site, including the dates of cover crop planting, cover crop termination, maize planting and fertilization, as well as the methods of planting and fertilization.

Daily weather inputs of precipitation, relative humidity, and minimum and maximum air temperature were retrieved from the University of Kentucky Agricultural Weather Center (http://weather.uky.edu/), a nearby weather station located at the same experimental farm. Solar radiation data were estimated using the DSSAT Weatherman 4.7.0.0 tool (Richardson, 1981, Jones, 2003). Daily wind speed data were obtained from the Lexington Bluegrass Airport, located approximately 13.7 km from the field site.

2.3.2. *Soil physical parameter calibration*

Soil parameterization at each landscape position was based on soil samples for the top 0–60 cm, and soil survey for the deeper layers (Table 2; (Soil Survey Staff, 2020)). Soil saturated hydraulic conductivity (K_{sat}), volumetric water content at drained upper limit (DUL), lower limit (LL), and at saturation (SAT) were calculated from DSSAT pedotransfer functions, and further optimized by 10 cm soil layer to minimize error in prediction of observed soil water storage data. Slope was estimated based on analysis of LIDAR imaging from the Kentucky Department of Agriculture (KYFromAbove, 2017), and drainage class, curve number, soil albedo, and runoff potential were obtained from the USDA-NRCS (Soil Survey Staff, 2020). DSSAT simulates water run-off using these topographic inputs, but the model does not account for run-on from surrounding land. Thus, in the simulations, we assumed that all landscape positions received equal amounts of water input based only on the daily precipitation levels. The lack of water transport from one landscape position to another in the simulations likely matches a lack of water redistribution in the field study as well, which included sod buffers between the cropped areas at each landscape position (Fig. 1). However, the toeslope position in both the field study and in simulations may underestimate conditions of saturation under high precipitation and run-on in continuous cropland (Table 2).

2.3.3. *Parametrization of the DSSAT-Century for soil N mineralization*

The treatment receiving 0 kg N ha^{-1} after winter fallow at each landscape position was used to parametrize DSSAT-CENTURY. The CENTURY model requires parametrization of a stable, intermediate, and microbial organic C and N pools (Parton et al., 1994). The model requires input of the total organic C and N, and the fraction of stable organic C. The microbial C pool is calculated as 5% of the total non-stable C pool (1 – Percent Stable C). The intermediate pool is then calculated as the difference between 1 and the stable and microbial C pools. To initialize simulations, the stable fraction of C according to each soil texture and field cropping history was selected from recommended values in DSSAT v.4.7.1.001. Thereafter, the stable organic C pool was modified to minimize error in the prediction of total aboveground N content in maize at R1 and R6 in the treatment receiving 0 kg N ha^{-1}. To minimize carry-over of errors in the water and N balance during simulations of the fallow/cover crop-maize rotation, during calibration and model evaluation across all treatments, simulations were initialized at cover crop termination, and cover crop biomass and composition, as well as soil water storage and inorganic N at this time were provided as

Table 2
Measured, estimated, and calculated characteristics of soils used in simulations. Soil layers were provided to the model in 10 cm increments but are averaged and combined in this table for brevity.

Profile	Measured Inputs						Estimated Inputs	Model Generated Inputs[b]				
	Depth[a] cm	Clay	Silt	Org. C	Org. N	Bulk Density g cm^{-3}	Stable C Fraction %	LL	DUL	SAT	SRGF 0−1	K_{sat} cm hr^{-1}
		——	—— % ——	——	——			"——	% vol.	——"		
Summit	0−30	21.7	68.7	1.6	0.14	1.3	40.0	0.115	0.362	0.455	0.775	1.200
	30−60	42.8	44.4	0.3	0.03	1.3	56.7	0.260	0.450	0.500	0.123	0.090
	60−100	30.9	61.8	0.4	0.03	1.4	70.0	0.240	0.431	0.479	0.036	0.150
Backslope	0−30	24.6	63.5	1.8	0.16	1.2	90.5	0.128	0.413	0.497	0.902	1.275
	30−50	47.0	36.0	0.3	0.02	1.2	94.0	0.200	0.480	0.507	0.607	0.060
Toeslope	0−30	19.1	71.5	2.2	0.19	1.2	62.5	0.098	0.379	0.443	0.975	1.065
	30−60	25.0	67.0	1.2	0.11	1.3	73.3	0.207	0.442	0.498	0.177	0.383
	60−90	25.0	65.0	0.8	0.07	1.3	80.0	0.330	0.450	0.485	0.057	0.173
	90−150	28.0	60.0	0.5	0.04	1.3	90.0	0.262	0.404	0.477	0.005	0.075

[a] Measured soil properties were derived from collected soil samples for the top 60 cm and estimated from Soil Survey data (Soil Survey Staff, 2020) for deeper layers.
[b] LL: Lower limit, DUL: Drained upper limit, SAT: Saturated limit, SRGF: Soil root growth factor, K_{sat}: Saturated hydraulic conductivity.

an input.

2.3.4. Calibration of crop coefficients

Cultivar coefficients for the CERES-Wheat model were calibrated to match the observed aboveground biomass and N content at cover crop termination. Cultivar NEWTON in DSSAT v.4.7.1.001 was used to initialize simulations. To better match the amount of biomass and N content, the length of optimum temperature required for vernalization (P1V) was set to 52 days. Standard mature tiller weight (G3) was increased to 2.2 g, and the interval between successive leaf tip appearance (PHINT) was increased to 143 growing degree days (GDD). The goal of this calibration was to obtain an amount of biomass and N content similar to the observed but did not focus on having cultivar coefficients that closely described phenology, growth, and partitioning of a cereal rye crop.

Cultivar coefficients for CERES-Maize were calibrated utilizing data from the treatment receiving 270 kg N ha^{-1} following a winter fallow at the toeslope. This was done to minimize confounding effects of water and N stress and obtain crop growth coefficients closest to the real genetic potential for the hybrid used in our study. In addition, simulations were initialized at the time of cover crop termination to minimize carryover of error in the water and N balance from starting simulations the previous fall. Calibration of maize crop growth coefficients in CERES-Maize consist of six parameters: thermal time from emergence until the reproductive stage (P1), the days of delay in development per hour increase in photoperiod above 12.5 h (P2), thermal time from silking to maturity (P5), the maximum number of kernels per plant (G2), and the kernel filling rate during the linear grain filling stage (G3). Parameter P1 was optimized to match the simulated time of anthesis with the observed. Parameter P2 was set to 0 assuming limited photoperiod sensitivity in modern corn hybrids. The P3 parameter was modified to match the observed timing of physiological maturity. The PHINT parameter was then adjusted to match more closely the observed aboveground biomass at R1 and R6. G2 was adjusted to minimize bias in the prediction of the number of kernels per plant. Finally, the G3 coefficient was adjusted to reduce bias in the prediction of kernel size and yield. The final set of maize cultivar coefficients after calibration were 285 GDD, 0 days, 800 GDD, 1070 kernels per plant, 8.20 mg day^{-1}, and 38 GDD, for P1, P2, P3, G2, G3, and PHINT, respectively.

2.3.5. Model evaluation

After calibration utilizing data from the winter fallow treatments (treatments receiving 0 and 270 kg N ha^{-1}), model performance predicting maize yield, kernel number, aboveground biomass and N content, and soil water storage was evaluated across the different N fertilizer levels within each landscape position following a cereal rye cover crop. The statistics used to evaluate model performance were the root mean square error (RMSE), normalized root mean square error (NRMSE), and the Nash-Sutcliffe Efficiency Index (NSE) between observed and simulated data (Eqs. 1–3, respectively),

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (Simulated_i - Observed_i)^2}{n}} \quad (1)$$

$$NRMSE = \frac{\sqrt{\frac{\sum_{i=1}^{n} (Simulated_i - Observed_i)^2}{n}}}{\frac{\sum (Observed)}{n}} \quad (2)$$

$$NSE = 1 - \frac{\sum_{i=1}^{n} (Simulated_i - Observed_i)^2}{\sum_{i=1}^{n} (Observed_i - Observed_{Av})^2} \quad (3)$$

where $Simulated_i$ is the simulated value for R1 aboveground biomass, R1 aboveground N, R6 aboveground biomass, R6 aboveground N, maize yield, grain N content, unit kernel weight, or kernels per square meter, and $Observed_i$ is the respective observed value. $Observed_{Av}$ is the mean of the observed values for a respective parameter, and n is the number of observations. Lower values of the RMSE and NRMSE indicate greater agreement between modeled and observed data. The NSE can range from 1 to negative infinity, with positive values indicating the model is a better predictor than the average value of the observed data. Model evaluation and the calculation of model statistics was performed in R, using the base R functions and the HydroGOF package (Version 0.4.0, (Zambrano-Bigiarini, 2020) .

2.4. Sensitivity analysis with historical weather

Following calibration, a sensitivity analysis was performed using the DSSAT v.4.7.1.001 Sequence module to simulate crop rotations. Simulations were run using historical weather data from 1989 to 2019 with soil profiles for each of the three landscape positions in our field study. In addition, simulations were conducted under different soil N fertility levels, which were generated by varying N fertilizer rates and soil organic matter levels. The two N fertilizer scenarios consisted of the Kentucky recommendations for maize crops on well drained soils (Recommended N, 155 kg N ha^{-1}) and the highest rate present in our study (High N, 270 kg N ha^{-1}). The soil organic matter levels consisted of the baseline, which reflected the conditions present at our site (Baseline Fertility, 1.9–2.2 % OC in top 15 cm), and a site with ~50 % less soil organic C and N (Low Fertility, 1.2 % OC in top 15 cm). Simulations started with cover crop planting in the fall each year and ended at maize harvest the following year. Simulations lasted only one rotation, and soil water storage and inorganic N were reinitialized before the start of the next simulation based on observed soil samples collected from our field trial in October 2018. Planting date and date of fertilizer applications were kept fixed on the same day of the year across all model runs. The model was not run continuously for the thirty-year period, but rather reinitialized in the fall of every year for a total of 30 one-year rotations. Thus, our study is intended to evaluate the seasonal effect of cover crops and not long-term rotational effects.

To study the effect of years with lower vs. greater precipitation than the average, we classified years into three categories based on the summer precipitation: wet, average, and dry. These distinctions were made according to the 33rd and 66th percentile of the cumulative maize growing season precipitation (from planting to harvest) for the thirty years of weather data. The specific precipitation thresholds were $<$ 559 mm for dry, 559–697 mm for average, and $>$ 697 mm for wet. As temperature and precipitation are inherently linked, we did not set a temperature threshold when categorizing individual years. To quantify which factors explained a greater amount of the yield variability in simulations, the simulated yield for both the low and baseline soil organic matter scenarios were analyzed using an ANOVA with landscape position, cover crop, N fertilizer level, precipitation category and their interactions considered as fixed effects in the model, and year of the simulation considered as a random factor. Analysis was performed using the aov function from the stats package in R (v 4.0.2, (R Core Team, 2020)).

Based on the results of this sensitivity analysis, we decided to focus on the baseline soil organic matter conditions under the recommended N application to investigate spatial and temporal yield variability. We examined the coefficient of variation (CV) in simulated yield across all landscape positions and weather years under both cover cropping scenarios. We also examined the CV in simulated yield within specific landscape positions and precipitation categories. To quantify the yield gap due to water limitation and the percentage of years that underwent water stress, the sensitivity analysis was re-run under automatic irrigation when actual crop available water in the top 30 cm of soil dropped below 60 % of available capacity. In the soils that were calibrated for this simulations, the 60 % thresholds that triggered irrigation were 11.35 cm of water in the summit, 9.74 cm of water in the backslope, and 11.79 cm of water in the backslope. When the amount of water dipped below these thresholds, irrigation automatically raised the amount of soil water to the DUL. Irrigated and non-irrigated treatments were then compared, and years that experienced a yield loss greater than 10 % were considered to have undergone yield penalizing water stress and characterized as such.

3. Results

3.1. Model performance and comparison to field experiment

3.1.1. Cover crop biomass and N content

The cereal rye cover crop in our field experiment accumulated an average of 3225 kg dry matter ha^{-1} and 60 kg N ha^{-1} prior to termination in 2019 (Fig. 2A). Cover crop biomass and N content were similar across landscape positions in our experimental year (P = 0.31 and 0.34, respectively). After calibration of the cultivar coefficients for CERES-Wheat, the model simulated aboveground biomass and N content values that were within one standard deviation of the observed means for 2019 (Fig. 2A). Simulations across 30 years of weather data showed large interannual variability in cover crop biomass, ranging from 1051 kg ha^{-1} to 7485 kg ha^{-1}. Averaged across 30 years, the simulated cover crop biomass production was 16 % higher in the toeslope than the summit and backslope positions (Fig. 2A).

3.1.2. Maize growth and N content

Maize grain yield in our field experiment varied significantly among landscape positions (P < 0.001), ranging from 6.3 Mg ha^{-1} on the backslope to 12.2 Mg ha^{-1} on the toeslope (Fig. 2B). There were no effects of cover crop (P = 0.30) or N fertilizer rate (P = 0.28) on maize yield. Following calibration of CERES-Maize crop growth coefficients with treatments under winter fallow, the model simulated maize grain yield values that were within one standard deviation of the observed means for 2019 (Fig. 2B). In addition, maize aboveground biomass, kernel number, and yield in the calibration dataset (i.e., the winter fallow treatment) were predicted with a relatively low nRMSE ranging from 8 to 9% and a positive model efficiency ranging from 0.32 to 0.86 (Fig. 3A). When the model was evaluated in treatments following a cereal rye cover crop, nRMSE in the prediction of aboveground biomass, kernel number and yield increased in all cases compared to calibration, but the values were still within acceptable levels (nRMSE = 12–21 %; Fig. 3B).

After soil organic matter pools in DSSAT-CENTURY were optimized using the data from fallow treatments receiving 0 kg N ha^{-1}, the model predicted aboveground N content with an acceptable nRMSE across all N fertilizer rates and landscape positions in maize after fallow (13.7 %–18.3 %) (Fig. 3A). The model was more efficient at capturing the increase in aboveground N after fertilizer application at R1 (NSE = 0.86) than at R6 (NSE = -0.20). However, the overall RMSE in prediction of aboveground N at R6 was still low (40.6 kg ha^{-1}) and mainly associated with an over prediction of N content in treatments receiving the highest N fertilizer rate (Fig. 3A). Similar to fallow treatments, the model was more efficient at predicting maize aboveground N at R1 (NSE = 0.86) than at R6 (NSE = 0.17) in maize following the cereal rye cover crop. Overall, the model was efficient at predicting difference in yield and R1 and R6 biomass, and aboveground N at R1 across treatments. However, predicted aboveground N content at R6 and grain N content showed a larger response to the N fertilizer rates applied than the observed data and were over predicted on average under the highest N fertilizer applications.

3.1.3. Soil moisture dynamics

Landscape position and cover crop significantly affected soil water storage in our field experiment (P < 0.001). The cover crop treatment had significantly higher soil water storage in the top 0.5 m than the winter fallow treatment (Fig. 4). As soil water storage decreased during the summer of 2019, soil water was higher during late maize reproductive stages in the backslope and toeslope positions when following a cereal rye cover crop (Fig. 4, Supplemental Fig. 1). Calibration and evaluation model simulations captured well the decrease in soil water during the maize growing season with a low RMSE ranging from 5 to 23 mm. Model simulations also captured the greater soil water storage following cereal rye early in the maize season, but not during seed filling, when both cover crop and fallow treatments had similar simulated soil moisture (Fig. 4). In the maize after fallow treatment used for calibration, the NSE for the prediction of soil water storage ranged from 0.89 to 0.91 in the top 0.5 m, and from 0.68 to 0.79 in the lower 0.5 m. In the maize after cover crop treatment, NSE values ranged from 0.89 to 0.96 in the top 0.5 m, and 0.61 to 0.68 in the lower depths, with the summit having an outlier NSE value of -3.7. Soil water storage at lower

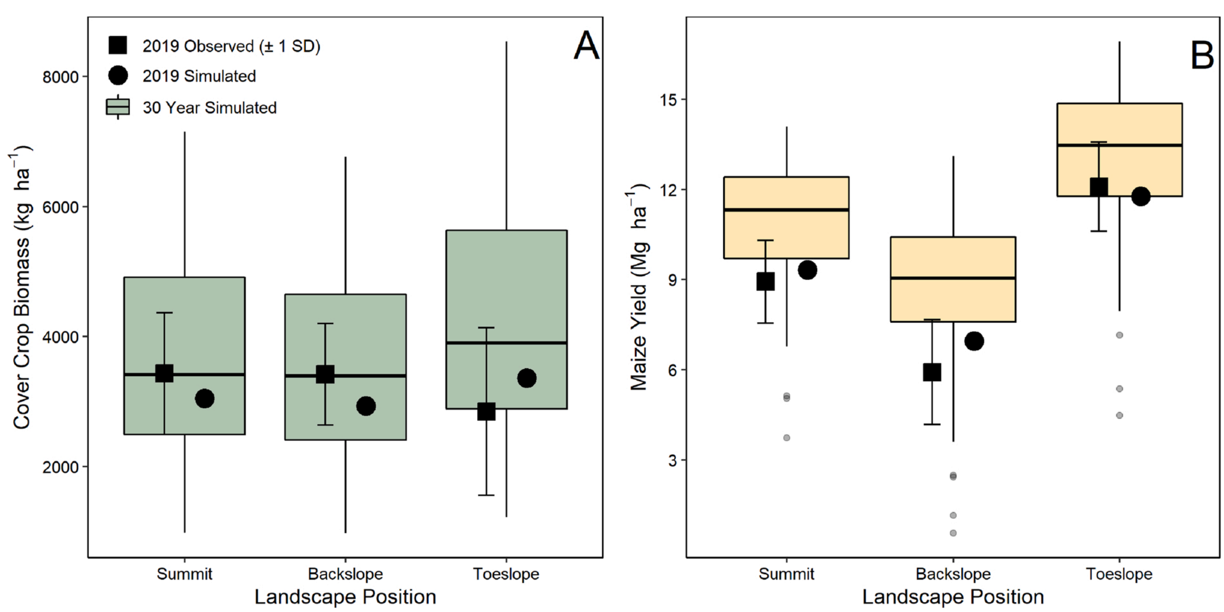

Fig. 2. A.) Observed and simulated rye cover crop aboveground biomass at termination (A), and maize grain yield (B). Closed symbols represent observed and simulated data for experimental trials in 2019, error bars on observed data represent ± 1 standard deviation. Boxplots show data from 30-year simulations with historical weather data (1989 – 2019).

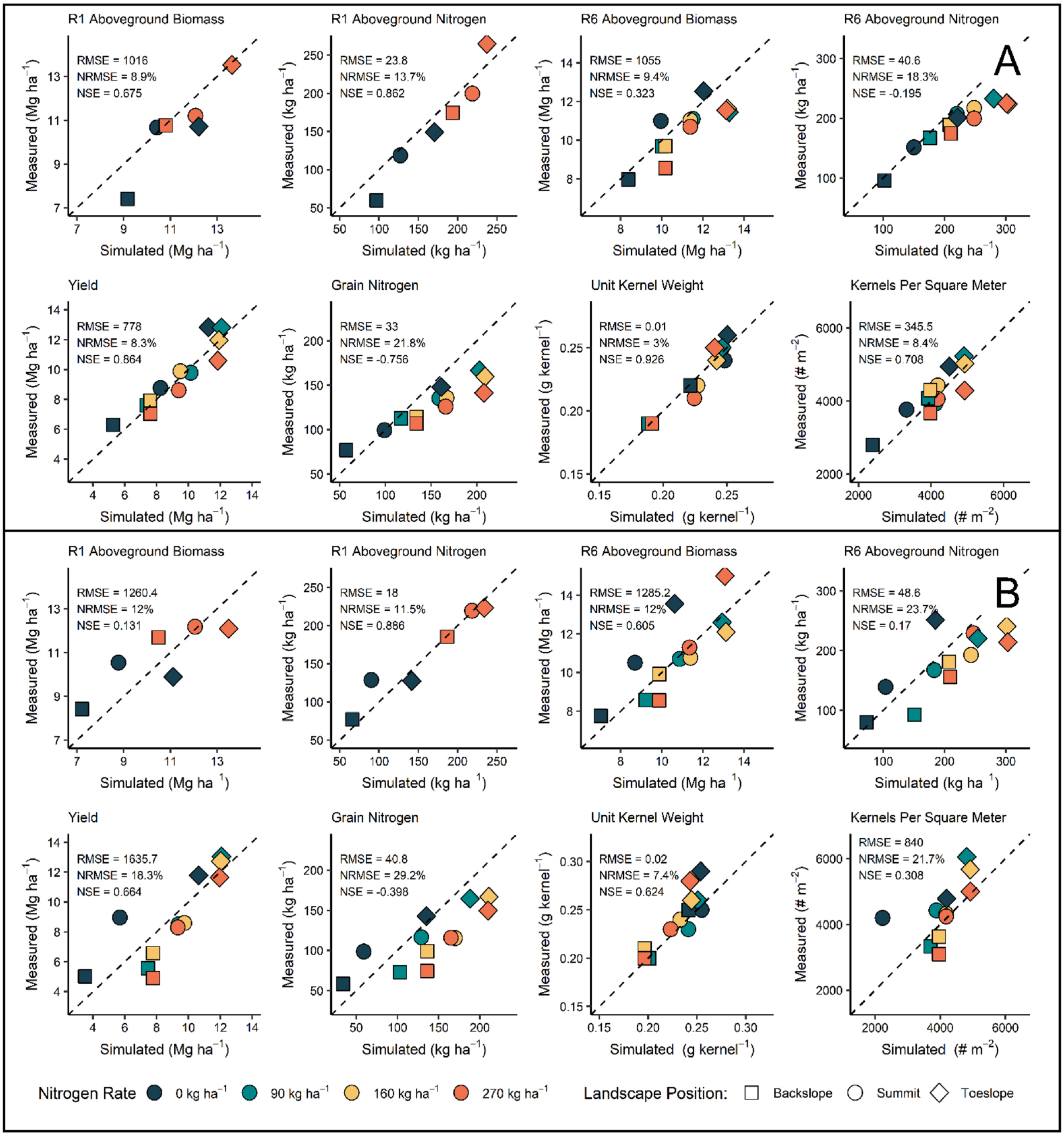

Fig. 3. Observed and simulated maize aboveground biomass and N content at R1 and R6, grain yield, grain N content, unit kernel weight, and kernels per square meter in maize after fallow (A) and maize after a cereal rye cover crop (B). Different symbols show data by landscape position and N rate. Maize aboveground biomass and N content at R1 was only sampled in treatments receiving 0 and 270 kg N ha^{-1}.

depths experienced less variability throughout the year, which led to decreased NSE values relative to the top 0.5 m, but low NRMSE and RMSE values in lower depths indicate strong model agreement.

3.2. *Sensitivity analysis of weather and management effects on simulated maize yield*

Variation in simulated yields across 30 years was attributed mainly to the weather classification based on precipitation (i.e. dry, average, wet), which accounted for 32–35 % of the total sums of squares (SS) in the ANOVA (Fig. 5). Landscape position, and its interaction with precipitation category, were the second and third most important factors in determining maize yields under the baseline soil organic matter scenario, and the second and fourth most important factor in explaining yield variability in the low soil organic matter scenario. The effect of landscape position and its associated interactions accounted for 28 and 31 % of the total SS for the baseline and low fertility soil organic matter soil, respectively. The cover crop main effect and its interactions with other factors explained more variability under the baseline soil organic matter model than in the low soil organic matter model (0.8 % and 0.5 %, respectively). Interestingly, N fertilizer rate and its interactions with other factors did not explain yield variability in the baseline soil conditions (0.2 % of total SS). Under the low fertility model, the effect of N rate and its interaction with other factors increased (2.8 % of total SS), but still explained a relatively low percentage of the yield variability compared to the effects of landscape position, precipitation category, and their interactions. Full ANOVA tables for the low and baseline soil organic matter level analyses can be found in Supplemental Section 1.

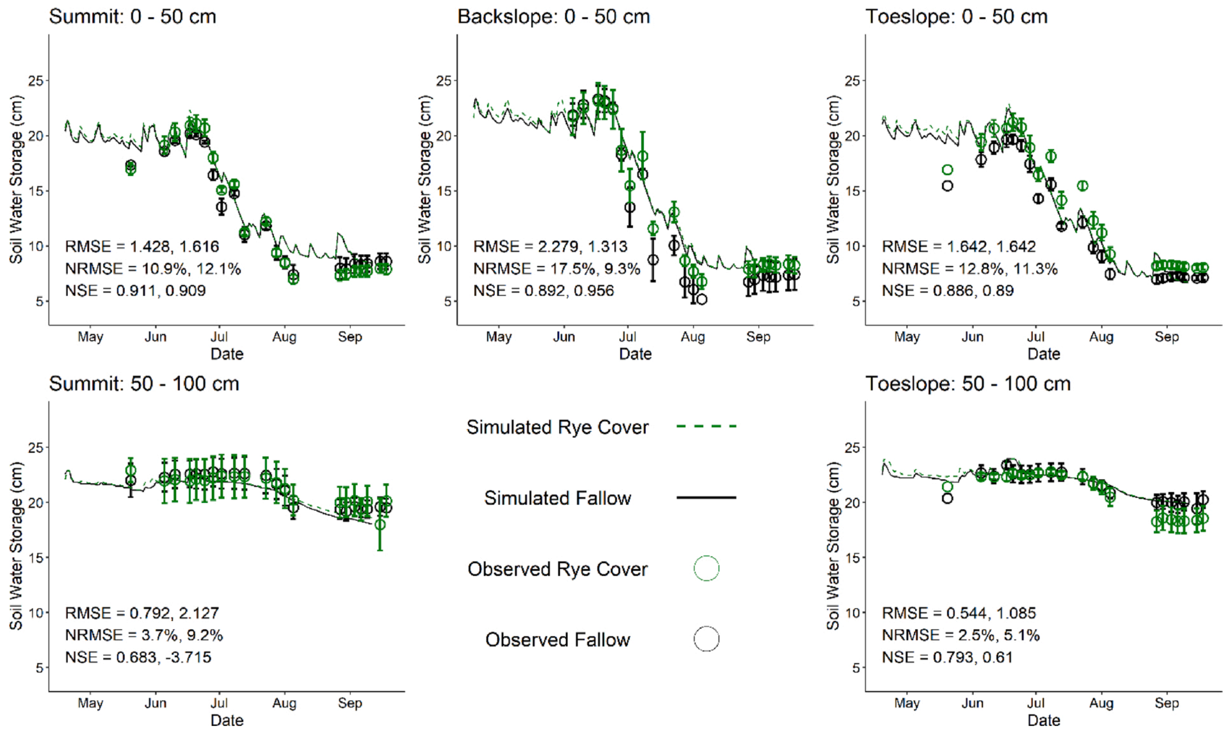

Fig. 4. Observed and simulated total soil water in the top (0-50 cm) and bottom (50-100 cm) soil profile at each landscape position in maize after fallow and after a cover crop during 2019 experimental trial. Soils in the backslope position did not extend beyond 50 cm. Error bars show the standard error in the observed data. Statistics for model performance are presented for fallow treatment and rye treatment, respectively.

Because precipitation category and landscape position were the most important sources of variation while N fertilizer level had a minor impact, subsequent discussion of results is focused on the landscape position x weather x cover crop interaction under a single baseline soil condition and a common recommended maize N rate for our study region, 155 kg N ha^{-1}.

3.2.1. *Cover crop effects on simulated maize yield and yield stability*

Simulated maize yield averaged 10.7 Mg ha^{-1} across weather years, landscape positions, and cover crop treatments. Average simulated maize yields were 12 % higher and 25 % lower during wet and dry years, respectively. Across weather scenarios and cover crop treatments, the toeslope was consistently the highest yielding landscape position (12.9 Mg ha^{-1}), followed by the summit (10.7 Mg ha^{-1}), and then the backslope (8.5 Mg ha^{-1}) (Fig. 6). Across the 30-year dataset, the addition of the cover crop increased the average yield by 2.2 %, though the magnitude of this effect varied by landscape position. Simulated yields increased by 6.1 % in the backslope and by 1.1 % in the toeslope for maize following the cereal rye relative to the winter fallow and were similar between cover crops and winter fallow in the summit position. When averaged across landscape positions, the cover crop treatment increased maize yield by 10.9 % during dry years, 1.4 % during average years, and decreased yields by 2.3 % during wet years. The greatest benefit of the cover crop on simulated maize yields was during dry years on the backslope (24 % increase), while the greatest reduction in yield due to the cover crop was during wet years on the backslope (4% decrease).

The yield-variance plots revealed that while maize yields shifted slightly when following a cover crop, the variance in yield among years was reduced for all landscape positions (Fig. 7A), and the variance among landscape positions was reduced in dry and average years (Fig. 7A and B). Across all precipitation categories, the stabilizing effect of the cover crop on interannual yield variability was strongest on the backslope position and was similar on the summit and the toeslope positions (Fig. 7C). When combined spatial and interannual variability were examined for each precipitation category, the greatest reduction in CV was observed during dry conditions. There was a moderate reduction in CV during average precipitation years, and the rye cover crop had no effect on maize yield CV during wet years (Fig. 7D). The coefficient of variation for yields among all landscape positions and weather years decreased from 33 % to 26 % when a rye cover crop was added to the rotation (Fig. 7E).

3.2.2. *Cover crop effect on frequency and size of simulated water-stress yield gap*

Our weather classification in wet, average, and dry years based on relative precipitation amounts did not consider if the maize crop experienced water stress. Thus, simulations under automatic irrigation during the maize growing season were used to calculate the yield gap due to water stress relative to non-irrigated simulations. Our results indicated that the summit and toeslope positions experienced a water-stress yield reduction greater than 10 % in 6 out of the 30 years examined (Fig. 8A). The backslope position was much more prone to water stress, undergoing >10 % yield reductions in 17 of the 30 years of weather data in maize following fallow. The addition of a cover crop into the rotation reduced the percentage of years with a >10 % water-stress yield gap by four years in the backslope, but did not reduce frequency of water stress in the summit or toeslope positions (Fig. 8A). In addition to decreasing the frequency of water stress, the presence of a cover crop decreased average water stress yield gap in all three landscape positions, reducing average yield loss by 985 kg ha^{-1} yr^{-1} (34 % of average water-stress yield loss) in the backslope, 296 kg ha^{-1} yr^{-1} (26 % of average water-stress yield loss) in the summit, and 198 kg ha^{-1} yr^{-1} (17 % of average water-stress yield loss) in the toeslope position (Fig. 8B).

3.2.3. *Cover crop effects on simulated water balance and water stress*

Cover crop transpiration during the winter growing season reduced the amount of soil water at cover crop termination by 8.8 mm in the top 50 cm of soil on average compared to winter fallow. However, this small deficit was typically overcome by the time of maize planting two weeks

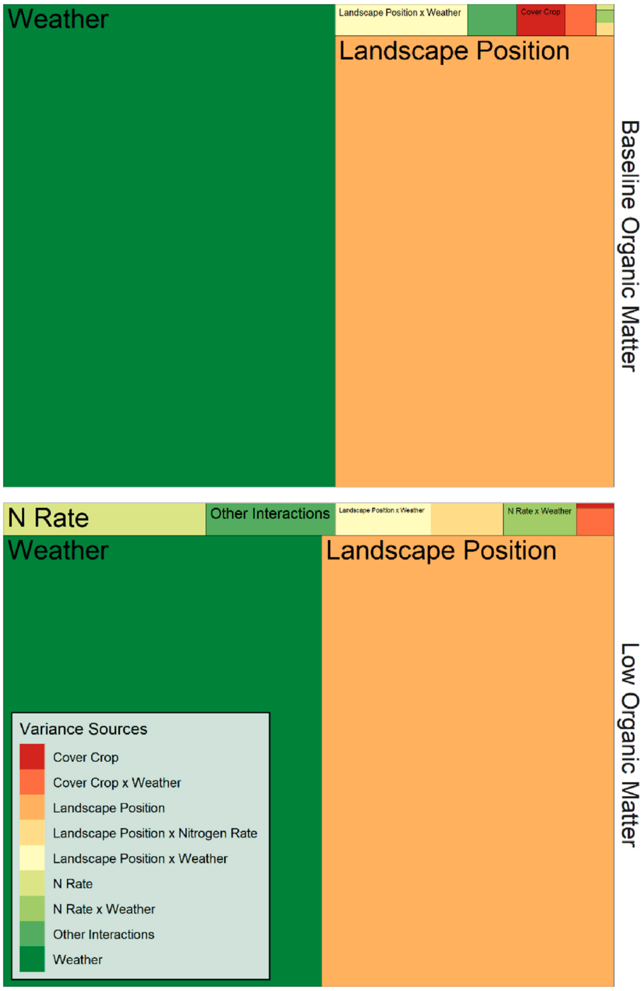

Fig. 5. Treemap indicating the apportionment of sums of squares within the ANOVA models for the baseline soil fertility and the low fertility treatments. Larger areas within the treemap correlate with greater percentage of sums of square apportioned to a particular model term.

later via spring precipitation (Supplemental Fig. 2).

The presence of cover crop residue reduced water losses through evaporation during the maize growing season by 72–91 mm depending on the landscape position and precipitation category. The largest reduction in evaporation occurred during wet years (87 mm reduction). During dry and average years, the reduction in total soil evaporative loss was similar across all landscape positions (74 mm and 79 mm reductions, respectively) (Table 3). In addition to the reduction of evaporation, the presence of cover crop residue also reduced the amount of runoff by 20–76 mm in the summit and backslope positions depending on weather class (Table 3). In contrast, runoff was similar across cover crop treatments in the toeslope (Table 3).

Averaged across the 30 years of weather conditions, the rye cover crop increased maize transpiration in each landscape position. The effect was greatest on the backslope (16.8 mm increase), moderate at the summit position (7.2 mm increase), and generally negligible at the toeslope (2.4 mm increase) (Table 3). The effect was greatest during dry years, where the presence of cover crop residue increased transpiration by 18.4 mm across landscape positions. During average and wet years, the increased transpiration due to cover crop residue was only 7.7 mm and 0.2 mm, respectively. These average increases were driven largely by the cover crop effect in the backslope position across precipitation categories (Table 3). The presence of the cover crop residue increased the amount of soil water drainage from the bottom of the profile by 25–95 mm depending on the landscape position and precipitation categories (Table 3). Total drainage was greatest at the toeslope position, ranging from 60 mm in dry conditions under fallow to 190 mm during wet conditions under the cover crop. The greatest increase in drainage due to the cover crop was observed in the backslope (48–95 mm) and in wet years across landscape positions (50–85 mm).

Although the effect on maize total transpiration was relatively small in absolute terms, a consistent decrease in the growth water stress index, defined as a ratio between actual and potential evapotranspiration, was observed (Fig. 9). Growing a rye cover crop decreased the intensity of water stress during maize flowering and grain filling under dry years. As precipitation during the maize growing season increased, the difference in water stress between the fallow and cover crop treatment was delayed till later in the season, but was still evident across landscape positions during average years, and in the backslope during all precipitation categories. During the vegetative stage of growth, the cover crop increased the excess water stress index indicating excessive soil water not conducive to plant growth. This occurred in the backslope across all

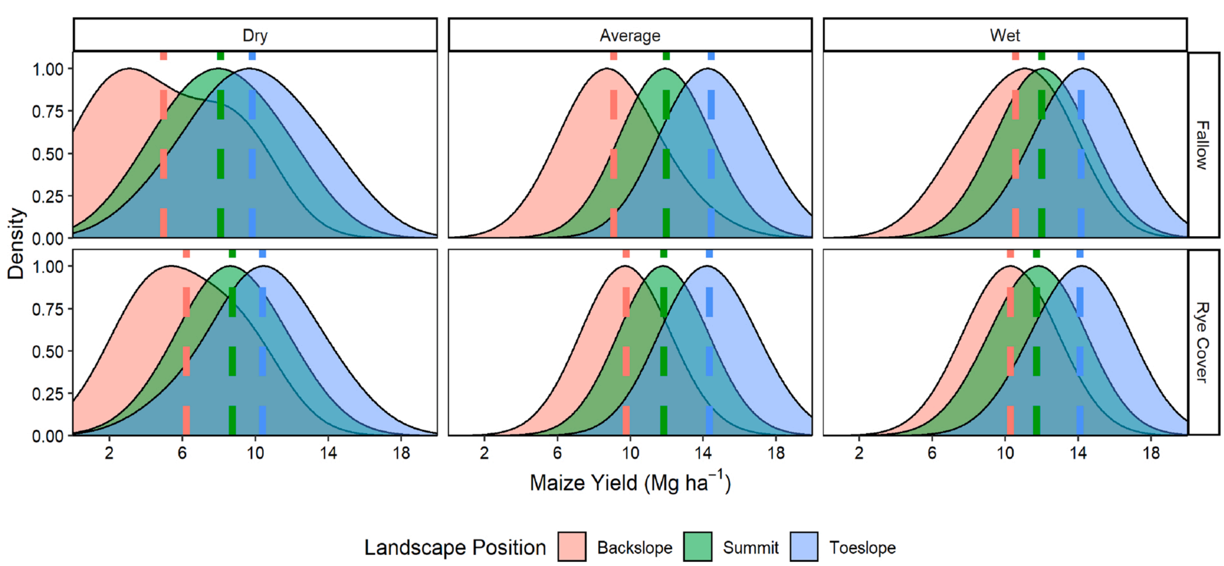

Fig. 6. Smoothed density plots of maize yield at different landscape positions for different cover crop treatments and precipitation categories. Dashed lines indicate the mean yields for each distribution.

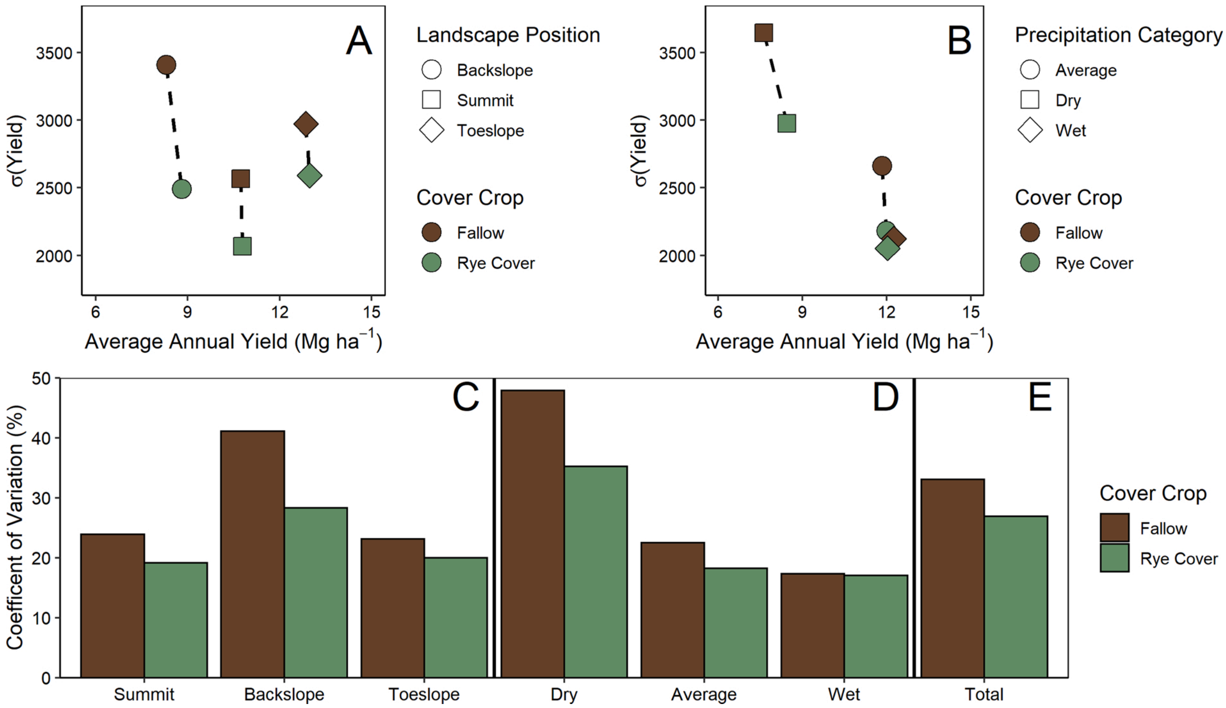

Fig. 7. Top: Maize grain yield vs. variance plot for the different landscape positions (A) and different precipitation categories (B).Dashed lines connect the fallow and cover cropped treatment within the same landscape position. σ^2(Yield) is equal to one standard deviation in kg ha^{-1}. Bottom: Yield coefficient of variation from 30-year simulations by landscape position (C), precipitation category (D), and total (E), of maize grown after fallow or after a cereal rye cover crop.

precipitation categories during the vegetative phase, and in the summit and toeslope during average and wet years (Fig. 9).

4. Discussion

4.1. Applications of DSSAT to simulate topography x weather x cover crop interactions

Crop model applications provide an opportunity to overcome limitations of agronomic trials by studying a wide array of management adaptations and environmental conditions. Our analysis, which focused on three contrasting landscape positions, indicated that process-based models can play a useful role in understanding and informing ecological processes that increase productivity and reduce sub-field variation in areas of complex topography. Our crop model simulations were particularly useful to overcome two main limitations in our field trial: i.) inability to test unlimited number of management options and soil fertility conditions, and ii.) inability to study the effect of year to year variability in environmental conditions. Our simulation study was also key to illustrating that spatial and temporal maize yield fluctuations in our study area are mainly associated with variability in water availability across years and landscape positions, and relatively less dependent on N cycling under recommended N fertilizer inputs, even under a low organic matter scenario and the presence of a cover crop. We used CERES-Wheat to simulate observed cereal rye cover crop growth in our study. Other studies have used crop models from different species than the cover crop to study water and N cycling in cover crop rotations (Adhikari et al., 2017; Li et al., 2008; Salmerón et al., 2014; Qi et al., 2011). The CERES-Wheat module used in our study offered the advantage of simulating the detrimental effect of water excess on plant growth processes (Mearns et al., 1996; Thorp et al., 2010). Cereal rye cover crop biomass and N content at termination in our 30 year simulations were within the range of those reported in field trials for our study region (Thapa et al., 2018), though timing of spring termination is a major source of variability when comparing biomass levels. Data from more years that include fall and spring destructive cover crop biomass and N sampling and soil water storage, including periods of excess water, would be beneficial to reduce uncertainty in cover crop predictions in our study area, where cover crops may experience high variability in soil moisture conditions ranging from water stress to saturation depending on the year and landscape position.

We found that the benefits of cover crop reported in our study were associated with increased water availability to maize during reproductive stages, due to a reduction of soil evaporation and runoff. While our observed data from 2019 showed a small 14 mm increase in soil water storage in the top 0.5 m of backslope and toeslope positions following the cover crop during late reproductive stages, this trend was not captured in our model simulations. Instead, model simulations in 2019 showed similar soil moisture across cover crop treatments (1–2 mm higher following rye compared to fallow), but an increase in crop transpiration by 9−10 m mm in the backslope and summit in maize after a cover crop compared to fallow. Precipitation during 2019 was insufficient to meet the crop evapotranspiration demand, leading to a pronounced depletion of soil water storage to a level close to the lower limit in the 0 to 0.5 m soil depth. DSSAT model simulations will assume that water is similarly available across the range of plant available water without considering water tension, and it is possible that this simplification was not able to capture soil water storage dynamics when soil moisture decreases to values close to the lower limit. It is interesting to note that increased water availability in cover crop treatments in 2019 did not result in significantly greater maize yields. Our explanation based on the simulations for this year, as well as observed soil moisture data and maize yield components, is that cover crop treatments experienced relatively greater excess water stress early on, that was compensated by greater water availability later in the season. This presumption is consistent with the higher incidence of excess water stress observed early in the season under cover crop treatments in our 30-year simulations. These results reveal an interesting interaction that should be further evaluated under different cover crop termination dates and residue management strategies. Optimized cover crop management recommendations may depend on different landscape positions to reduce the incidence of excess water stress while maximizing water

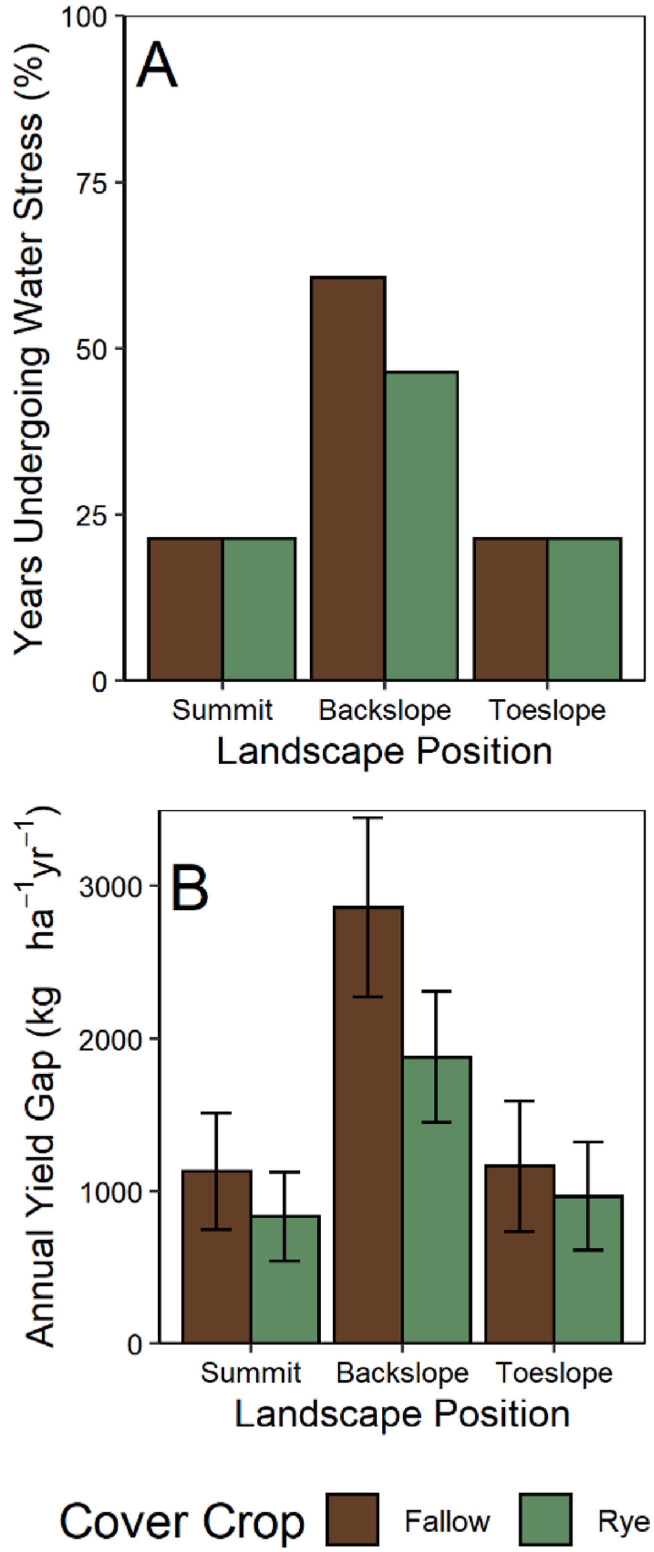

Fig. 8. Percentage of years undergoing 10 % or greater yield reduction due to water stress (A) and average annual yield gap due to water stress across all simulation years (B) by landscape position and cover crop treatment. Error bars indicate ± 1 SE.

savings for later in the season.

In our simulation results, the presence of the cover crop residue reduced soil water losses through runoff and evaporation. In particular, the presence of the cover crop residue led to a reduction in soil evaporation of 75 mm across landscape positions and climate conditions. This magnitude of decrease is consistent with another modeling study of a rye cover crop maize rotation using APSIM in a homogeneous field in Central Iowa (Basche et al., 2016a,b). Other modeling studies also found a greater reduction in soil evaporation during wet years following a rye cover crop than following winter fallow (Qi et al., 2011), similar to what we observed.

Soil water runoff is largely driven by the infiltration rate of soils and the time in which maximum infiltration is reached (Magdoff and Van Es, 2009). Previous research has shown that the addition of a cover crop residue increases the time which maximum infiltration is reached, consequently decreasing runoff losses (Blanco-Canqui et al., 2015). Results from our 30-year simulations showed a decrease in the amount of soil water runoff in the summit and backslope positions of up to 70 and 50 %, respectively, in maize after a cereal rye cover crop compared to fallow. This is in agreement with the effect of a rye cover crop on run-off rates found by (Zhu et al. (1989), in which a grass cover crop decreased the seasonal run-off by 44–53 % in a maize-soybean [*Glycine max* (L.) Merr] system. Beyond the immediate effects on soil water storage, this reduction in run-off provides additional benefits of reducing soil erosion and downslope nutrient losses that can occur during surface and subsurface runoff events, compounding the potential benefits of cover crops in sloping areas.

When following a rye cover crop, soil water drainage during the maize growing season increased by 37–94 mm compared to the winter fallow treatment. This effect was unexpected, and a consequence of the reduced soil evaporation and runoff after a cover crop, and high intensity of precipitation events concentrated during short periods in the spring, when crop evapotranspiration demand is still low. This increase in drainage may have important implications on N leaching losses and show an interaction with timing of N fertilizer application depending on weather and landscape position that should be addressed in further studies. There has been considerable work done on the effects of cover crops and their ability to limit winter drainage and N loss through winter transpiration, both field studies (Kaspar et al., 2012; Meisinger and Ricigliano, 2017; Strock et al., 2004), and modeling (Li et al., 2008). However, field and modeling studies evaluating residual effects of cover crop on drainage and N leaching during the next cash crop growing season are less frequent (Brandi-Dohrn et al., 1997; McCracken et al., 1994; Salmerón et al., 2014, 2010; Tonitto et al., 2006). It is possible that drainage in our simulations was overpredicted overall due to the methodology employed by the DSSAT model to capture downward water movement in the soil profile; a tipping bucket approach where water drains into lower layers as the upper limit of a given layer is reached (Jones et al., 2003). This methodology, though effective in capturing the soil water balance as a whole of a given system, may lead to error in drainage estimates (Meng and Quiring, 2008; Soldevilla-Martinez et al., 2013). This is especially relevant in humid climates where a large portion of spring rain is partitioned to drainage. However, further work to clarify and validate the effect of cover crop residue on drainage during the early stage of vegetative growth of the cash crop in humid and sub-humid regions is still needed, especially studies that employ weighing lysimeters or eddy-covariance flux towers. Similarly, well-balanced studies evaluating model predictions under different timing of water stress with observed data could further accelerate model evaluation and improvement to simulate yield variability in complex topography.

4.2. Cover crops effect on maize yield

We hypothesized that cover crops would reduce water and nutrient losses and increase productivity and yield stability in the rolling hill topography of our study region. Our simulation results support our original hypothesis, indicating that a cereal rye cover crop increased the 30 year average yield across landscape positions by 230 kg ha^{-1}, and reduced interannual variability in maize yields by increasing yields on the backslope by 6% across all years, and by 24 % in dry years. Overall,

Table 3
Simulated water balance components during maize growing season by landscape position, precipitation category, and cover crop treatment, and difference between cover treatments (cover crop – control).

Landscape Position	Precipitation Category	Treatment	Evaporation	Difference	Runoff	Difference	Transpiration	Difference	Drainage	Difference
			mm							
Summit	Dry	Fallow	133	−76	28	−20	294	16	44	37
Summit	Dry	Rye Cover	58		8		310		82	
Summit	Average	Fallow	154	−80	37	−28	354	5	56	61
Summit	Average	Rye Cover	73		10		360		117	
Summit	Wet	Fallow	147	−87	78	−46	356	0	120	85
Summit	Wet	Rye Cover	60		32		356		205	
Backslope	Dry	Fallow	133	−72	75	−39	236	29	22	48
Backslope	Dry	Rye Cover	61		36		266		69	
Backslope	Average	Fallow	159	−80	105	−52	307	19	26	69
Backslope	Average	Rye Cover	79		53		325		95	
Backslope	Wet	Fallow	148	−86	180	−76	335	2	59	95
Backslope	Wet	Rye Cover	63		104		337		154	
Toeslope	Dry	Fallow	124	−73	9	−4	311	10	60	26
Toeslope	Dry	Rye Cover	51		5		321		86	
Toeslope	Average	Fallow	138	−77	11	−1	361	−1	85	38
Toeslope	Average	Rye Cover	61		10		360		124	
Toeslope	Wet	Fallow	142	−91	50	4	356	−2	140	50
Toeslope	Wet	Rye Cover	51		54		355		190	

the presence of cover crop residue reduced the CV in maize yields across landscape position and weather years from 33 % to 26 %. Only 5% of maize acreage in Kentucky is under irrigation, and thus maize grown in this area is highly subject to year-to-year variability in precipitation patterns and spatially varying soil characteristics. Our simulations indicate that, when following fallow, maize yield would be reduced by water stress by 10 % or more in 17 out of 30 years on the backslope, and in 6 out of 30 years on the summit and toeslope. The cover crop decreased the number of water-limited years to 13 years on the backslope. Thus, our results suggest that cover crops may be an important ecological intensification tool to increase productivity in rainfed environments with shallow soils.

Recent work on yield stability in maize cropping systems has identified topographic depressions as unstable zones due to near-average yields under low rainfall and below-average yields under high rainfall (Martinez-Feria and Basso, 2020). In contrast, we found that our lowest lying landscape position, the toeslope, was consistently the highest yielding landscape position, and had the lowest CV among landscape positions averaged across cover crop treatments. This discrepancy highlights that the landscape position effects on yield and temporal yield stability observed in one region may not transfer well to another. It is possible that our simulations under-predicted the potential negative effects of water saturation in the toeslope associated with run-on water during wet years. Also, the regional differences may be driven by differences in soil forming factors. For example, the soils of Kentucky are naturally well-drained because they are underlain by karst, while many soils in the Central US do not have well-developed drainage features and are therefore more prone to excess water. In our simulation studies, the

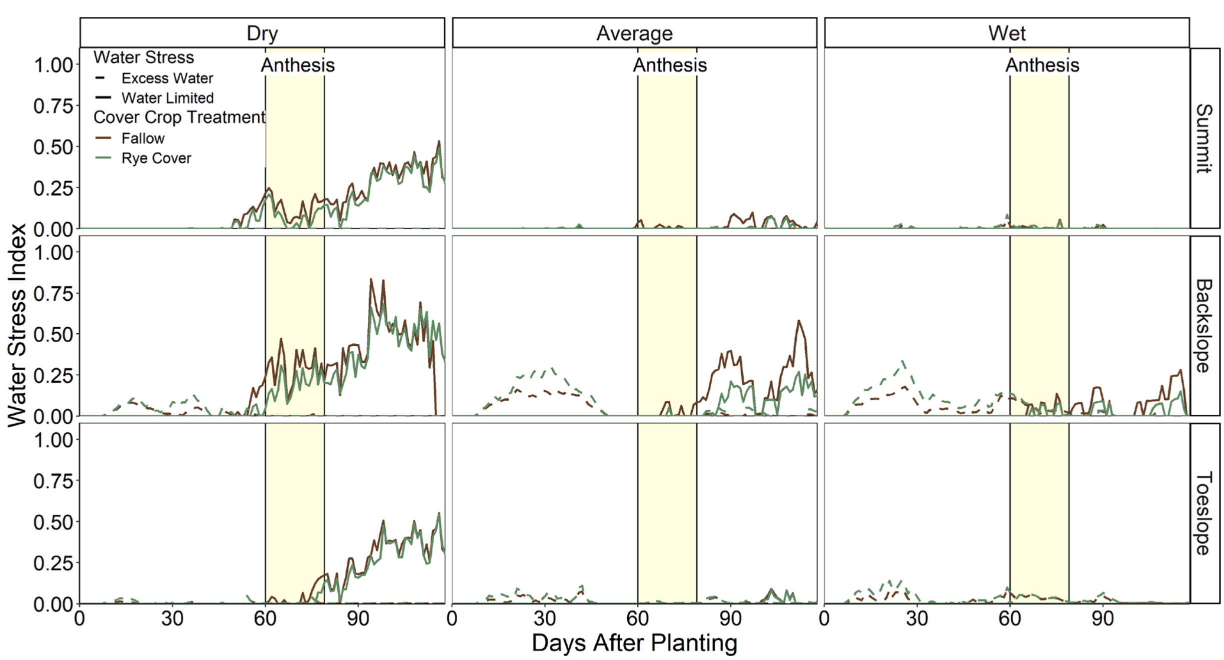

Fig. 9. Simulated daily excess and limited water stress index during the corn growing season by weather scenario (dry, average, and wet) and landscape position for each cover crop treatment. Data averaged across 30-year simulations. The shaded yellow bar indicates the range of simulated anthesis dates across the 30-year simulation study (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

incidence of stress caused by water excess increased under the cover crop treatments, although the overall effects of cover crops were positive due to increased water during seed filling. However, it is possible that cover crops may lead to yield losses in wet years and landscape positions with poor drainage or increased run-on.

It was interesting to find that winter transpiration of cover crops did not typically decrease water availability for maize, with differences in soil moisture between cover crops treatments usually disappearing before planting. However, this finding may not hold true in drier locations. Our study site in Central Kentucky is located in a sub humid climate zone and receives ~1100 mm of rainfall on average. Studies in more arid and semi-arid zones have indicated that the reduction in soil water loss through evaporation and run-off reduction does not make-up for the loss through cover crop transpiration and leads to increased water stress for the cash crop following a winter cover crop (Blanco--Canqui et al., 2015; Unger and Vigil, 1998) . It is likely that maize grown at other locations within our study area that receive less precipitation may experience water stress after a cover crop in dry years. Cover crop management, in particular termination timing, could help palliate potential negative effects associated with water stress and increase yield stability in these locations (Alonso-Ayuso et al., 2014).

4.3. Study limitations and future research

Several research groups have pointed out that despite the benefits of cover crops, there are still barriers to adoption (Roesch-McNally et al., 2018). One key limitation to adoption is the perception that the integration of cover crops may decrease yields. The results of our simulation study indicate that the addition of a cover crop rarely has a detrimental effect on maize yields and can actually increase yields in areas of the landscape that are more prone to water limitation during especially dry years. The lack of substantial difference in yield between maize following a cover crop and maize following fallow at the summit and backslope during average years is in line with other studies that have researched the impact of cover crops on crop yields and have found little to no effect under typical field settings (Basche et al., 2016a,b; Martinez-Feria et al., 2016b). However, our simulation study does not account for the possibility of increased pest or disease pressure following rye, which can limit yields (Bakker et al., 2016), and could also underpredict yield reductions due to excess water. Farmers often experience reduced soil inorganic N after cover crops, and increased N stress due to the immobilization of plant available N during high C:N cover crop residue decomposition (Krueger et al., 2011). Our field site, because of its recent conversion from sod, did not appear to be substantially N limited. This allowed us to focus primarily on the hydrologic cycling aspect of the interactive effect of topography, cover crops, and climate. Further study is needed on how these three factors may influence biogeochemical cycling across space and time. When examined as a whole, our results highlight that cover crop experiments performed in uniformly high-yielding soils may underestimate the benefits of cover crops and make their use less appealing to producers. Continued research on the potential of cover crops to stabilize yields and increase resilience to climatic variability, especially in areas of complex topography, is critical to closing knowledge gaps about how these practices might function in large production settings.

5. Conclusions

In this study, we coupled field data and crop model simulations to quantify the effect of a winter cover crop on maize yields and their variability over space and time, to evaluate the potential of this management adaptation in rolling hill terrain, and to inform future experimental research. The majority of maize yield variability in our simulations was explained by weather and landscape position. The cereal rye cover crop reduced year to year variability in maize yield across all landscape positions, and increased average yields on the backslope, particularly in dry years. Maize following a cover crop tended to have less water limitation during reproductive stages but sometimes excess water during vegetative growth compared to maize following fallow. Our results suggest that a rye cover crop is one route toward ecological intensification in rolling hill terrain and that cover crop research conducted in topographically uniform research trials may overlook important benefits. Continued research on the effect of cover crops on the water balance during the cash crop growing season in areas of variable soil depth and complex topography is paramount to adapting these management strategies for ecological intensification of agricultural land.

CRediT authorship contribution statement

Sam J. Leuthold: Conceptualization, Formal analysis, Software, Data curation, Visualization, Writing - original draft. **Montserrat Salmerón:** Conceptualization, Software, Writing - review & editing, Funding acquisition. **Ole Wendroth:** Conceptualization, Writing - review & editing, Funding acquisition. **Hanna Poffenbarger:** Conceptualization, Supervision, Project administration, Writing - review & editing, Funding acquisition.

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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