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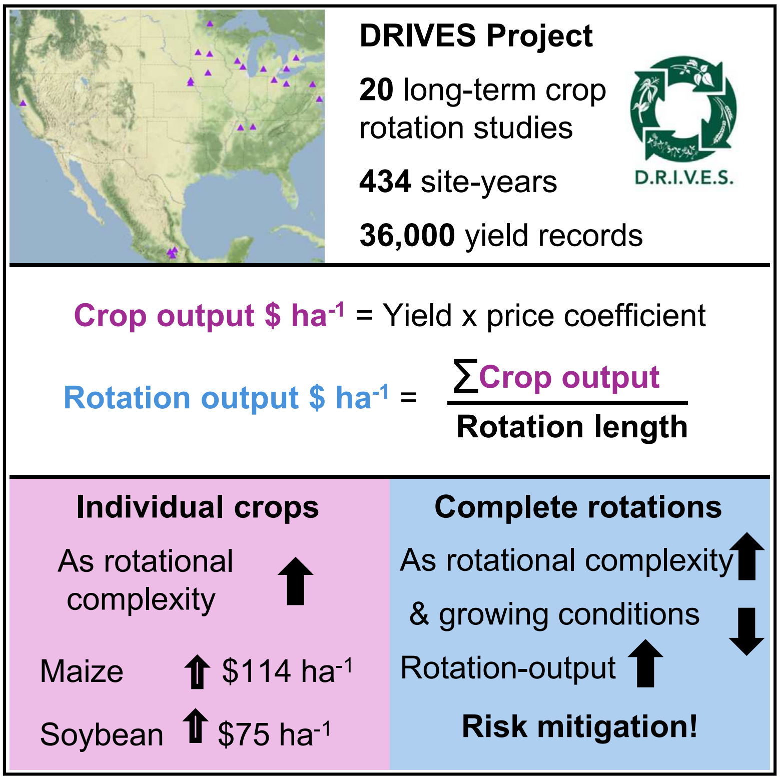
Rotational complexity increases cropping system output under poorer growing conditions

Graphical abstract



Highlights

- Data from multiple long-term crop rotation studies identify generalizable trends
- Quantifying portfolio effects entails assessing crops and complete rotations
- Corn and soybean output increased in more diverse crop rotations
- More diverse rotations performed better under poor growing conditions

Authors

K. Ann Bybee-Finley, Katherine Muller, Kathryn E. White, ..., Nele Verhulst, Brook Wilke, Timothy M. Bowles

Correspondence

ann.bybee-finley@ncsu.edu

In brief

Diversifying cropping systems enhances resilience to increasingly unpredictable weather and climate variability by stabilizing farm output. However, economic hurdles make adopting more diverse crop rotations challenging, particularly when producers are uncertain about the risk-reducing benefits of diverse rotations. This multiregion research examines long-term cropping system experiments with varying crop rotation diversity to quantify their productivity and risks under various growing conditions. The results provide needed information to assist farmers and policymakers in designing more resilient and productive cropping systems.

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Rotational complexity increases cropping system output under poorer growing conditions

K. Ann Bybee-Finley,[1,2,20,22,*] Katherine Muller,[1,20] Kathryn E. White,[1,3] Michel A. Cavigelli,[1,21] Eunjin Han,[3]
Harry H. Schomberg,[1,21] Sieglinde Snapp,[4,21] Frederi Viens,[5,6,21] Adrian A. Correndo,[7] Leonardo Deiss,[8] Simon Fonteyne,[4]

(Author list continued on next page)

[1]USDA-Agricultural Research Service, Sustainable Agricultural Systems Laboratory, Beltsville, MD 20705, USA
[2]Department of Crop and Soil Sciences, North Carolina State University, Raleigh, NC 27695, USA
[3]USDA-Agricultural Research Service, Adaptive Cropping Systems Laboratory, Beltsville, MD 20705, USA
[4]International Maize and Wheat Improvement Center (CIMMYT), El Batán 56237, Mexico
[5]Department of Statistics, Rice University, Houston, TX 77005, USA
[6]Department of Statistics and Probability, Michigan State University, E. Lansing, MI 48848, USA
[7]Department of Plant Agriculture, University of Guelph, Guelph, ON N1G 2W1, Canada
[8]School of Environment and Natural Resources, The Ohio State University, Columbus, OH 43210, USA
[9]Department of Agronomy and Plant Genetics, University of Minnesota, St. Paul, MN 55108, USA

(Affiliations continued on next page)

SCIENCE FOR SOCIETY Agriculture faces increasing challenges from unpredictable weather. Diversifying crops over space and time can help maintain productivity and enhance the resilience of agroecosystems by enabling farmers to adapt to environmental risks. We quantified crop output under different rotations using 20 long-term datasets. By examining crops and complete rotations, we quantified the portfolio effect under various growing conditions. Assessing outcomes using multiple metrics, soil types, and cropping systems reduces uncertainty about adopting more diverse rotations, crucial under increasing production risks from adverse weather. This will inform stakeholders—from farmers to policymakers to lenders—in supporting cropping systems, policies, or programs that reduce risk. Moving forward, our efforts can enhance our understanding of the value of diverse crop rotations and insights connecting agricultural practices to societal outcomes from farm economic performance to consumer nutritional choices.

SUMMARY

Growing multiple crops in rotation can increase the sustainability of agricultural systems and reduce risks from increasingly adverse weather. However, widespread adoption of diverse rotations is limited by economic uncertainty, lack of incentives, and limited information about long-term outcomes. Here, we combined 36,000 yield observations from 20 North American long-term cropping experiments (434 site-years) to assess how greater crop diversity impacts productivity of complete rotations and their component crops under varying growing conditions. Maize and soybean output increased as the number of species and rotation length increased, while results for complete rotations varied by site depending on which crops were present. Diverse rotations reduced rotation-level output at eight sites due to the addition of lower-output crops such as small grains, illustrating trade-offs. Diverse rotations positively impacted rotation-level output under poor growing conditions, which illustrates how diverse cropping systems can reduce the risk of crop loss in a changing climate.

INTRODUCTION

Diversifying crops over space and time is one of the strategies proposed to enhance the resilience of agroecosystems under an increasingly uncertain climate.[1] Crop rotations are the most common form of crop diversification in industrialized agroecosystems.[2] Rotations can be diversified by adding annual crops, cover crops, perennial crops, or some combination of the former

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Axel Garcia y Garcia,[9] Amélie C.M. Gaudin,[10] David C. Hooker,[11] Ken Janovicek,[7] Virginia Jin,[12] Gregg Johnson,[9] Heather Karsten,[13] Matt Liebman,[14] Marshall D. McDaniel,[14] Gregg Sanford,[15] Marty R. Schmer,[12] Jeffrey Strock,[16] Virginia R. Sykes,[17] Nele Verhulst,[4] Brook Wilke,[18] and Timothy M. Bowles[19,21]

[10]Department of Plant Sciences, University of California, Davis, Davis, CA 95616, USA
[11]Department of Plant Agriculture, University of Guelph, Ridgetown, ON N0P 2C0, Canada
[12]USDA-Agricultural Research Service, Agroecosystem Management Research Unit, Lincoln, NE 68583, USA
[13]Department of Plant Science, The Pennsylvania State University, State College, PA 16801, USA
[14]Department of Agronomy, Iowa State University, Ames, IA 50011, USA
[15]Department of Plant and Agroecosystem Sciences, University of Wisconsin – Madison, Madison, WI 53706, USA
[16]Department of Soil, Water, and Climate and Southwest Research and Outreach Center, University of Minnesota, Lamberton, MN 56152, USA
[17]Department of Plant Sciences, The University of Tennessee, Knoxville, TN 37996, USA
[18]W.K. Kellogg Biological Station, Michigan State University, Hickory Corners, MI 49060, USA
[19]Department of Environmental Science, Policy and Management, University of California, Berkeley, Berkeley, CA 94720, USA
[20]These authors contributed equally
[21]Senior authors
[22]Lead contact
*Correspondence: ann.bybee-finley@ncsu.edu
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to a simplified rotation. Rotations with high diversity have been shown to support multiple ecosystem services, including carbon sequestration,[3,4] pest suppression,[5,6] and protection of water quality.[7,8] Important for considering trade-offs or synergies between environmental benefits and food production, diverse rotations can also increase crop yields.[2,9]

Long-term data are critical, as the impact of crop rotations requires multiple cycles to take effect[10] and responses are often conditioned by other management practices (e.g., fertility or tillage regimes), soils, and climate.[11–14] Using data from multiple long-term experiments across spatial gradients can help generalize findings beyond the conditions from a specific context. Past long-term, multisite studies assessing the impact of rotational complexity on yields have often focused on the response of an individual crop across multiple locations.[11,12,15,16] However, because of their focus on single crops, such studies are unable to discern the potential benefits or trade-offs of increasing rotational complexity at the level of the complete rotation, nor do they demonstrate whether all crops in a rotation respond similarly. To our knowledge, no long-term, multisite studies have attempted to understand the effect of changing the rotation on the performance of both the complete rotation and its component crops simultaneously.

Synthesizing multiple experiments to understand how rotational complexity influences rotation and crop performance poses major challenges. Rotational complexity must be defined in a meaningful way across different production systems. Crop rotations can be analyzed based on their composition (e.g., species, number of species, functional groups, and sequence order) and length.[17] We elected to describe rotational complexity using a continuous rotational complexity index (RCI), based on the number of species and the length of the rotation, as done by Bowles et al.[11] Responses can be defined based on ecological (i.e., focus on the biophysical) or agronomic (i.e., focus on production management) priorities.

Assessing yield responses for complete rotations requires converting to a common unit that can be directly compared between crops, as yield inherently differs across crops (literally comparing apples to oranges). Many metrics are available to evaluate crop rotation effects, such as units of energy, nutritional value, efficiency of resource use, and gross or net returns. Metric selection is a subjective choice[18] that is constrained by data availability. Sanford et al.[13] conducted rotation-level analysis after converting maize (*Zea mays* L.), soybean (*Glycine max* [L.] Merr), and forage yields to units of human-available calories from milk and soybean oil. In a long-term rotation study in Iowa, net returns were used to assess economic performance at the rotation level by calculating gross returns and determining production costs.[19–21] Since each metric provides only a partial assessment of a given system,[18] different metrics reveal different trade-offs across cropping systems. For example, Snapp et al.[22] showed that more diverse rotations reduced grain yields but increased grain quality.

Converting yield on a weight basis (kg ha^{-1}) to output on a dollar basis ($ ha^{-1}) using market valuation does not require assumptions about end-use (unlike, e.g., nutritive value) or require additional, site-specific data that can be challenging to obtain (e.g., production expenses required to calculate net returns). Analyzing the effects of rotational complexity using a metric based on output is conservative because it situates rotations in the current agrifood system that incentivizes simplified rotations, such as federal crop insurance programs that support risk-taking.[23] With our analysis, a more complex rotation needs to outperform a simplified rotation to show beneficial outcomes.

Benefits from rotational complexity are driven by multiple mechanisms that occur on different scales. Yields of different crops with complex rotations are buffered against exposure to stress, since the crops in a rotation have different phenologies that may reduce exposure to the same stressors.[24] This buffering results in a portfolio effect whereby the net yield variation of all crops in a rotation is reduced compared with the average variation of the individual crops.[25] Functional differences among species (e.g., plant traits) can further enhance the portfolio effect by positioning plants to access different pools of resources[26] and allowing for differential responses to stress,[27] including pests, weeds, and diseases.[6,28] Rotations that contain perennial or cover crops enhance soil health by reducing periods with bare soil[14] and supplying resources in the form of root exudates and decomposing biomass that help build soil organic matter.[29] Increases in soil health observed under complex rotations[30] can reduce the impact of stressors on crop production, for example by increasing the water-holding capacity of soil.

Here, we analyzed the output of complete rotations and individual crops using 434 site-years of data from 20 long-term cropping systems experiments in North America that are a part of the Diverse Rotation Improves Valuable Ecosystem Services (DRIVES) Project. Our goals were to assess output (\$ ha^{-1}) responses for complete rotations and their component crops to better understand potential benefits and trade-offs associated with increased rotational complexity (number of species and rotation length) under varying growing conditions. We represented growing conditions with an environmental index (EI) based on site-year output and accounting for management differences.[31] We used Bayesian multilevel models to quantify output response to rotational complexity (RCI) and growing conditions (EI) and their interaction (RCI:EI) while accounting for additional management practices (e.g., fertility and tillage regimes). Complementary to regional analyses of specific crop production systems, our cross-site synthesis permitted us to gain understanding about how rotational complexity affects output across regions, systems, and growing conditions. We found that output of individual crops (maize and soybean) tended to increase with greater rotational complexity, while results for complete rotations varied among sites depending on rotation composition. This result showed that rotation composition drove rotation-level output more than individual crop performance. However, we were unable to detect differences in rotation-level responses among diversification strategies (i.e., additions of annual, cover, perennial crops, or a combination to a baseline rotation). As to assessing effects on yield risks, we found that rotational complexity improved rotation-level output under poor growing conditions across sites. This result demonstrates a portfolio effect in which diverse rotations help mitigate the risk of crop loss. Our work on crop rotations provides a partial assessment of cropping system performance based on a single performance metric across multiple long-term experiments. Nevertheless, by quantifying rotation-level outcomes, we demonstrated that greater rotational complexity most likely does not harm—and can benefit—individual crop outcomes. We also demonstrated that diversifying crop rotations can mitigate rotation-level losses, particularly from the threat of increasingly adverse growing conditions in a changing climate.

RESULTS

Synthesizing a cross-site legacy dataset

To analyze the effect of rotational complexity on the performance of individual crops and complete rotations, we combined data from 20 long-term cropping systems experiments (Table S1). Detrended historical yields (kg ha^{-1}) were converted to output (\$ ha^{-1}) using inflation-adjusted averages[32] so that different crops could be combined into complete rotation output (for details see experimental procedures, Figure S11, and Notes S1 and S2). Converting yield to output on a dollar basis increased the relative importance of crops with comparatively low biomass and high price coefficients, such as soybean, thereby reducing differences among crops (Figure 1). Crop-level models were constructed for maize, soybean, winter wheat (*Triticum aestivum* L.), and spring small grains (barley [*Hordeum vulgare* L.], oats [*Avena sativa* L.], spring wheat, and triticale [× *Triticosecale* Wittmack]). Rotation-level output included the crops described in the individual crop models as well as other crops that did not meet our criteria for individual crop analysis (i.e., present in more than one site with at least two rotations at a site). Because rotation-level output was averaged from individual crop output, the composition of crops in a rotation was an important driver of differences in rotation-level output. Of the 20 sites, seven had output for perennial forages, five had winter wheat, two had soybean, one had spring small grains, one had cotton (*Gossypium hirsutum* L.), one had dry bean (*Phaseolus vulgaris* L.), and one had sorghum (*Sorghum bicolor*) that were accounted for in the rotation-level model but were not present in the individual crop models because they were only present in a single rotation within a site (e.g., perennial forages) or only grown at a single site (e.g., cotton). Non-maize continuous monocultures were excluded from the rotation-level analysis so that the model reflected changes in diversity from a common starting point and the results were agronomically relevant.

Sites differed in their underlying yield potential due to climatic, soil, and management factors. Average maize yield ranged from 3.9 Mg ha^{-1} at sites MD and Mex3 to 10 Mg ha^{-1} at sites IA and WI1. Average soybean yield ranged from 1.6 Mg ha^{-1} at site TN2 to 3.3 Mg ha^{-1} at site Can2. Average spring small grain yield ranged from 2.1 Mg ha^{-1} at site NE2 to 4.0 Mg ha^{-1} at site Mex1. Average winter wheat yield ranged from 3.2 at site MI to 4.6 Mg ha^{-1} at site Can2.

Fifteen of the 20 long-term experiments contained additional management treatments that were either crossed or nested with crop rotation treatments. Based on their experimental designs, we defined a set of management subgroups within each site to isolate the effects of crop rotation from the effects of other management practices (Table S3 and Note S3). Most management subgroups were tillage and fertility treatments. Unless otherwise indicated, crops were managed with standard practices for fertility, tillage, and pest management.

Crop rotations ranged from continuous monocultures to integrated annual grain and perennial forage systems (Figure 2). The dataset contained 57 unique rotations (Table S2). Sites had an average of three rotations per site. The shortest rotation was 1 year and the longest rotation 6 years, with a median of 3 years per rotation. Sites generally used rotations that represented production practices in their region. This resulted in the presence of a common set of crops across sites (Figure 2 and Table S2). Rotation sequences tended to alternate crops with different functional traits; thus, longer rotations encompassed greater functional diversity (Figure 2). For modeling purposes, rotational complexity was quantified as a continuous metric (RCI) that used the number of species and rotation length (Equation 1). The smallest range of RCI (1.0–1.4) was at site Mex3, which added a cover crop to continuous maize monoculture. The largest range of RCI (1.0–4.9) was at site MI, which ranged from a maize monoculture to a 4-year rotation with three annual crops and cover crops. Across all sites, RCI tended to have a right-skewed distribution, with 65% of rotations having an RCI of 3 or less.

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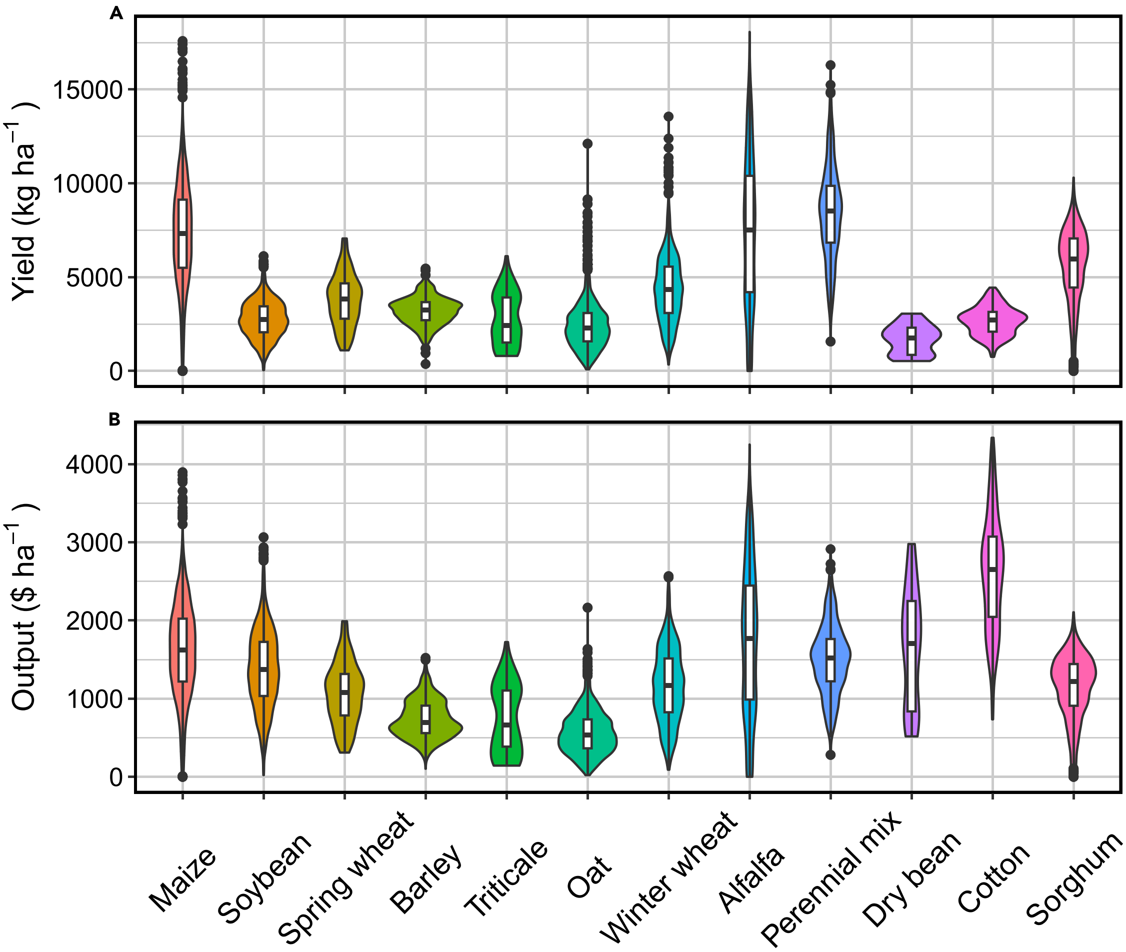

Figure 1. Crop yields to dollar output conversion for analyzing complete rotations

Crop yield on a dry-weight basis (A) was converted to output on a dollar basis (B) using NASS price data adjusted for inflation (Note S1). Violin plots show the probability density distribution of the data. Boxplots within violin plots denote the median, first, and third quartiles.

We defined six crop diversification strategies to help understand the practices of altering rotational complexity (Table 1). These strategies were mutually exclusive such that each site was categorized into one diversification strategy. Strategies were defined by whether diversity was increased by adding annual, cover, or perennial crops, or a combination. Some strategies were more often employed across sites than others. For example, only two sites diversified their rotations by adding cover crops to an annual crop, whereas eight sites added both annual and cover crops. Strategies that encompass more sites represented a wider range of growing conditions (Table 1).

Effects of rotational complexity on output

To determine the effects of rotational complexity on output, we constructed Bayesian multilevel models containing two terms of interest and varying intercepts to account for site and management differences. The main effect term (RCI effect) described how rotational complexity, as quantified by RCI, influenced output while growing conditions were held constant. The second term of interest (EI:RCI effect) described how the RCI effect responded to growing conditions, as quantified by EI. The EI approximated growing conditions by averaging output among rotations in the same site and management subgroup within a year. Thus, EI represented a baseline output due to growing conditions other than rotation. We obtained posterior estimates for the RCI and EI:RCI effects at the population and site levels (Figure 3 and Table S4) and aggregated by diversification strategy (Table 2). Unless specified otherwise, effects were reported as significantly above or below zero based on 95% Bayesian credibility intervals.

Complete rotations showed a wider range of responses to rotational complexity and growing conditions than individual crops (Figure 3 and Table S4). Of 19 sites, complexity did not change output in five sites, increased output in six sites (RCI effect >0), and decreased output in eight sites (RCI effect <0). Due to mixed outcomes across sites, rotational complexity did not change output at the population level (Table 2). Sites showed a common trend in how the effects of complexity changed over growing conditions (EI:RCI effect). On average, rotation-level output increased by +$11 ha^{-1} per unit RCI as EI decreased by $-$100 ha^{-1} (EI:RCI effect <0, Table 2). In sites where rotational complexity decreased output, this decrease was smaller

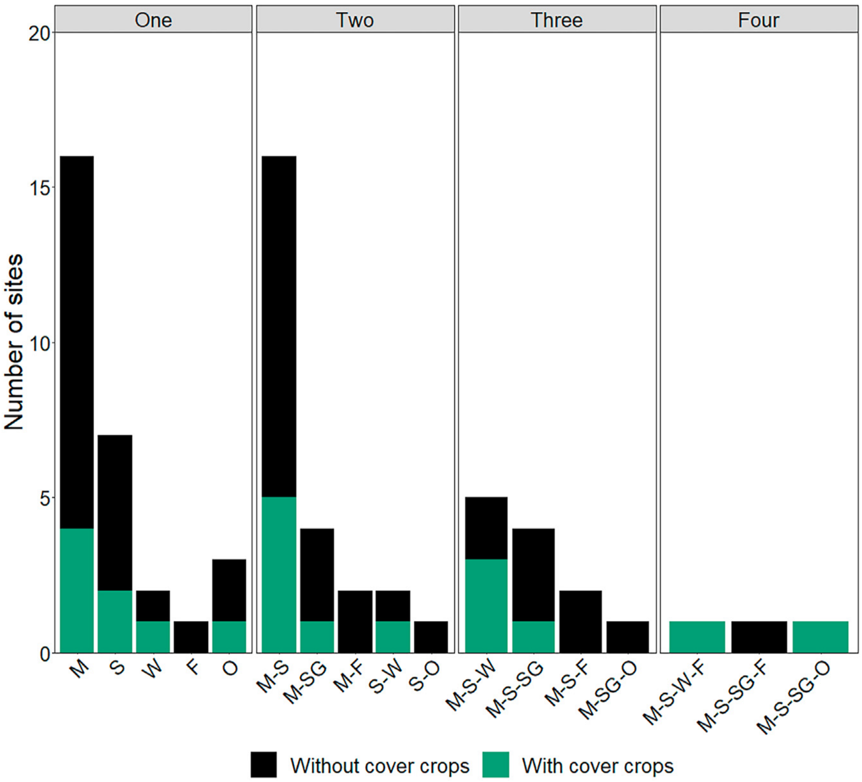

Figure 2. Frequency of crop rotations
Crop rotations are categorized by panels to indicate length in years (one, two, three, four). Crops are maize (M), soybean (S), spring small grains (SG), winter wheat (W), perennial forages (F), and other (O), which refers to dry beans (*Phaseolus vulgaris* L.), sorghum (*Sorghum bicolor* L. Moench), or cotton (*Gossypium hirsutum* L.). Additional details about crop rotations at each site are presented in Table S2.

under poorer growing conditions. In sites where complexity increased output, this increase was greater under poorer growing conditions. The extent to which growing conditions changed the effects of rotational complexity was evident in 7 of 19 sites (EI:RCI effect <0). These results suggest that complex rotations can mitigate environmental risk by improving output under less-favorable growing conditions.

Output of individual crops improved or did not change with increasing rotational complexity (Figure 3 and Table S4). On average, maize and soybean output increased by +\$114 ha^{-1} and +\$75 ha^{-1} per unit RCI (median estimate, RCI effect >0, Table 2). Rotational complexity improved output in 14 of 19 sites for maize and in 7 of 11 sites for soybean (RCI effect >0, Table S4). Rotational complexity increased maize and soybean output to a greater degree under better growing conditions, contrary to results for complete rotations. On average, the change in output per unit of RCI increased by +\$1.70 ha^{-1} (maize) and +\$1.60 ha^{-1} (soybean) when average output (EI) increased by \$100 ha^{-1} (median posterior estimates, EI:RCI effect >0, Table 2). Rotational complexity improved output to a greater degree under good growing conditions in 3 of 19 sites for maize and 1 of 11 sites for soybean. Although these effects were statistically significant, the extent to which growing conditions altered the effects of rotational complexity on individual crop output was seven times smaller than for complete rotations. Population-level responses for maize and soybean output captured trends that were not detectable at individual sites.

Inferences about effects of rotational complexity on winter wheat and spring small grain output were limited by the small number of observations (three sites for spring small grains, four sites for winter wheat, Table S2). At one site (Can1), winter wheat output increased in more complex rotations (Table S4). Otherwise, winter wheat output did not vary with rotational complexity, nor did the effects of complexity change with growing conditions (Figure 3 and Table 2).

Generally, effects of rotational complexity and the influence of growing conditions varied more among sites than among diversification strategies (Figure 3 and Table 2). Solely adding annual crops produced the greatest increase in complete rotation, maize, and soybean output (Table 2). Adding annual crops increased rotation-level output by an average of +\$110 ha^{-1} (median posterior estimate, RCI effect >0 at 92% probability), whereas all other diversification strategies produced no change or marginally decreased rotation-level output (Table 2). Adding annual crops increased maize and soybean output by +\$200 ha^{-1} and +\$128 ha^{-1}, respectively (median posterior estimate, RCI effect >0). The increase in output from this strategy was 100% greater for maize and 20% greater for soybean compared to any other strategy (Table 2). Diversifying with annual and perennial crops was more beneficial under poor conditions than under good conditions (EI:RCI effect <0, Table 2). On average, rotation-level output increased by +\$41 ha^{-1} per unit RCI as EI decreased by −\$100 ha^{-1} (median estimate) when diversifying with annual and perennial crops, more than twice the median EI:RCI effect found with other strategies.

Comparison between complete rotations and individual crops showed that rotation composition outweighed the effects of rotational complexity on individual crop performance. Of the eight sites where rotational complexity decreased rotation-level output, maize output increased at six of them (Table S4). Decreased output at the rotation level, but increased output for maize and soybean, suggests that the consequence of adding lower-output crops in more diverse rotations outweighed the benefit to maize and soybean performance. Conversely, adding higher-output crops can augment benefits of rotational complexity at the rotation level beyond effects on individual crops. For example, at the TN1 site, rotational complexity increased rotation-level output but not maize output (Table S4), due to the presence of high-output cotton in more diverse rotations. At the MD site, rotational complexity improved rotation-level output by +\$238 ha^{-1} per unit of RCI compared to +\$64

Table 1. Description of diversification strategies used by sites

Strategy	Description	Site	(No. of management subgroups)
Annual	rotational complexity is increased by adding annual crops that are harvested	Mex1	(2)
		Mex2	(1)
		NE1	(6)
Cover	rotational complexity is increased by adding cover crops, which are not harvested, to annual crops	CA	(2)
		Mex3	(2)
Annual and cover	rotational complexity is increased by adding annual crops, cover crops, or a combination	Can2	(8)
		MI	(4)
		MN1	(1)
		MN2	(1)
		MN3	(1)
		NE2	(3)
		TN1	(2)
		TN2	(2)
Annual and perennial	rotational complexity is increased by adding annual crops, perennial crops, or a combination	OH1	(3)
		OH2	(3)
		WI1	(1)
		WI2	(1)
Annual, cover, and perennial	rotational complexity is increased by adding annual crops, cover crops, perennial crops, or a combination	Can1	(2)
		IA	(1)
		MD	(1)

ha^{-1} for maize (Table S4), due to the presence of high-output forages in more diverse rotations.

Predictions of output for each diversification strategy

To illustrate the practical implications of rotational complexity, we predicted output for complete rotations, maize, and soybean using the same statistical models (Figure 4; Equations 3 and 4). Spring small grains and winter wheat are shown in Figure S1. We used fixed increments of RCI from 1 to 3 to cover the range of rotational complexity most common in our dataset. Output incorporated all sources of uncertainty in our models but was adjusted to correct for the uneven distribution of sites across strategies (Table 1). We did not have the power to detect differences among diversification strategies with respect to adjusted predicted output.

Complete rotations showed larger responses to rotational complexity across conditions, compared with maize or soybean. Differential responses across conditions were most pronounced when adding only annual crops or a combination of annual and perennial crops to a rotation. Adding only annual crops improved rotation-level output in all conditions, although the increase in adjusted predicted output with RCI was not significant at the 95% probability level. Moving from RCI of 1–3, adjusted predicted output increased by +\$408 ha^{-1} under poor conditions and +\$111 ha^{-1} under good conditions with the addition of annual crops (median difference). These results were positive for poor conditions at the 77% Bayesian credibility level, which is greater than two-thirds odds of a positive outcome. Under good growing conditions, however, it was more likely than not that these results were not significant (<50% Bayesian credibility). Adding a combindation of annual and perennial crops decreased rotation-level output under good conditions and produced no change under poor conditions. Moving from RCI of 1–3, the median adjusted predicted output decreased by −\$44 ha^{-1} under poor conditions and by −\$674 ha^{-1} under good conditions with the addition of annual and perennial crops (median difference). These results were positive for good conditions at the 70% Bayesian credibility level, but not under poor conditions (<50% Bayesian credibility). No other strategies resulted in changes in rotation-level output related to changes in rotational complexity within or across growing conditions.

Compared with complete rotations, maize and soybean responded more consistently to rotational complexity across growing conditions. Although output at individual sites changed due to rotational complexity over growing conditions (Table S4), these changes were not apparent when sites were combined into diversification strategies (Table 2). Rotational complexity increased maize and soybean output to a similar degree across growing conditions. Solely adding annual crops to maize showed the greatest benefit, with output increasing by +\$400 ha^{-1} from an RCI of 1–3 (median difference). This increase was twice as great as the increase in other strategies, with the highest probability density of 80% above zero, compared with 20%–60% for other strategies. Compared with complete rotations and maize, soybean output showed only minor differences among diversification strategies.

Interactions between rotational complexity and fertility and tillage regimes

Management practices conditioned responses to rotational complexity. Generally, nitrogen (N) fertility treatments showed more pronounced and consistent differences in the effects of

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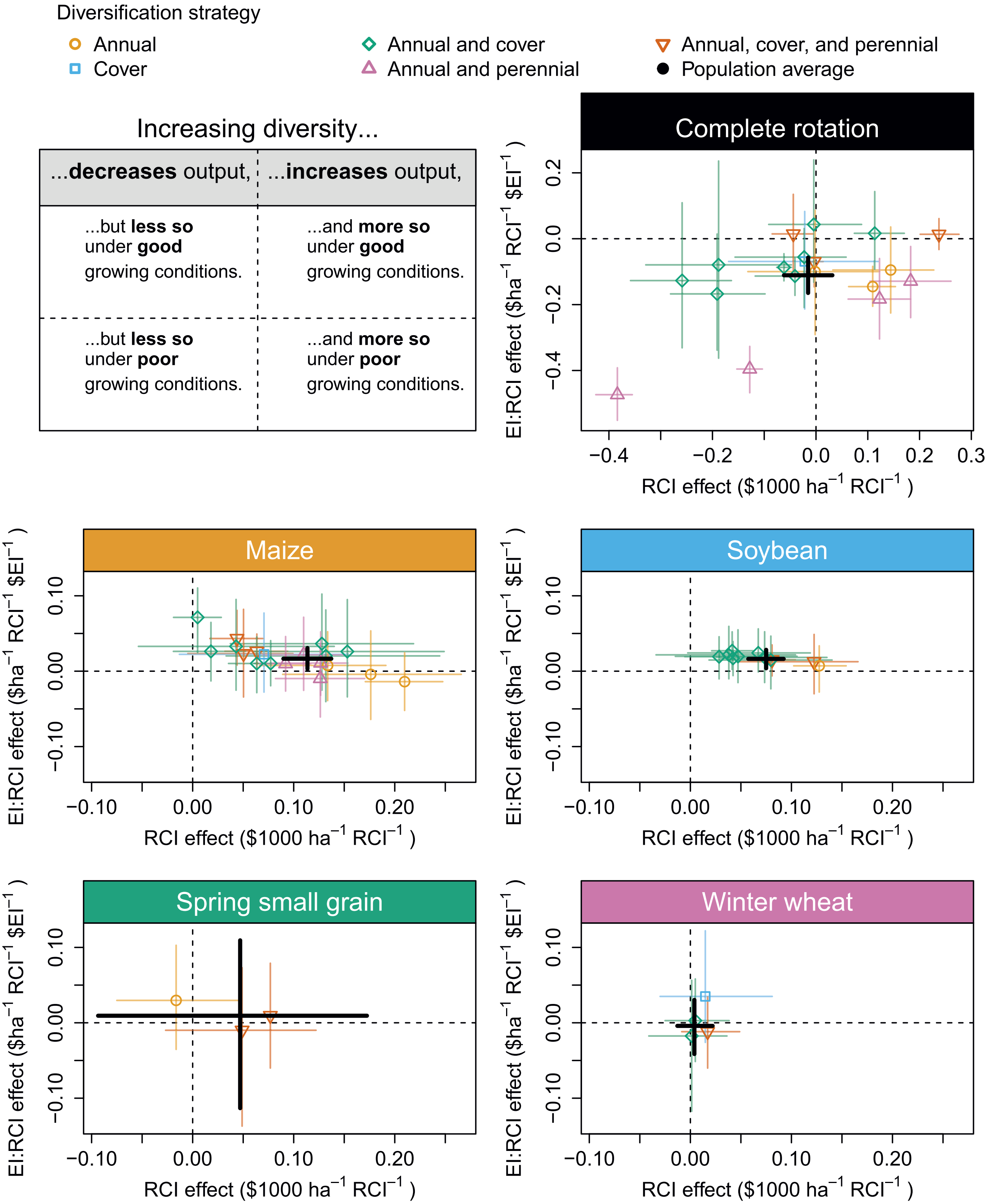

Figure 3. Model coefficients illustrating effects of rotational complexity on output

Rotational complexity is represented by a continuous index, RCI. Growing conditions are represented by an environmental index (EI), which is the average output within a site-year, accounting for management differences. The RCI effect is the change in output ($1,000 ha^{-1} RCI^{-1}) when growing conditions are held constant. The EI:RCI effect describes how the RCI effect changes with growing conditions ($ ha^{-1} RCI^{-1} $ EI^{-1}). Points represent the population-level (black) or site-level

(legend continued on next page)

rotational complexity on output than did tillage treatments (Note S4 and Figures S2–S10). Rotational complexity enhanced output under reduced synthetic N rates in all three sites, but this effect diminished as N rates increased (Note S4 and Figures S2–S5). Despite the positive effect of rotational complexity on output at low synthetic N rates, output was typically lower than complete rotations and individual crops fertilized with sufficient N (Figures S2–S5). Three of five sites with contrasting tillage treatments showed a difference in the effects of rotational complexity related to tillage intensity. However, the direction of these differences varied among sites and output types (Note S4 and Figures S6–S10). Here, results are likely influenced by differences in soil characteristics among sites.

DISCUSSION

We examined rotational complexity effects on crop- and rotation-level output with data from 20 long-term experiments using Bayesian analyses to quantify responses across growing conditions. In doing so, we were able to make inferences based on cross-site, population-level patterns, such as how rotational complexity affected rotation-level output under various growing conditions, and glean a generalized understanding about the effects of diversification. For the first time, we were able to quantify the portfolio effect across a wide range of sites that implemented diversification strategies suitable to their regions.

Rotational complexity improves or does not affect individual crop output

We found partial support for our hypothesis that crop-level output would increase with greater rotational complexity. For crops with sufficient data to analyze individually, crop-level output never declined in more complex rotations. Our multisite analysis showed that maize and soybean output usually responded positively to rotational complexity (14 out of 19 sites for maize, 7 out of 11 sites for soybean). These results align with Bowles et al.,[11] who used similar models to analyze maize yield data from 11 sites, five of which are in the DRIVES Project. They found a positive effect on maize yields with increased rotational complexity, with marginally greater benefits under good growing conditions. As with maize, previous work has found that rotational complexity often increased soybean yields compared with continuous monocultures.[33–36] We did not find clear effects of rotational complexity on small grains, in contrast to multiple long-term studies in Europe, which have found that winter and spring small grain yields improved with multi-crop rotations compared with continuous monocultures.[15,16] One reason for this might be the limited number of site-years for small grains at low rotational complexity represented across the DRIVES sites.

Rotation composition drives rotation-level output more than crop response

The effect of rotational complexity on crop-specific output likely reflected a response to improved biophysical conditions, including changes in soil properties and reduced pressure from weeds, diseases, and insect pests.[6,28,30,37] By contrast, rotational complexity effects on rotation-level output reflected differences associated with rotation composition, the portfolio effect, as well as the biophysical aspects that improved component crop performance. In 11 of 19 sites, rotational complexity increased or did not change rotation-level output. Moreover, rotation-level output tended to respond more positively to rotational complexity under poor growing conditions.

Our rotation-level analysis revealed trade-offs and benefits to rotational complexity due to rotation-level composition that were not discernible at the crop level. The reduced frequency of higher-output crops in more complex rotations reduced rotation-level output at eight sites. Small grain crops generally had lower yields compared to maize, and their market values on a dry-weight basis (\$282 and \$221 Mg^{-1} for wheat grain and maize, respectively) were insufficient to generate comparable output. In contrast, soybeans had yields similar to those of small grains (around 3 or 4 Mg ha^{-1}), but their higher market value (\$501 Mg^{-1}) resulted in output comparable to that of maize. Perennial crops either increased or decreased rotation-level output depending on the length of the forage stand. Rotation-level output decreased when adding a 1- or 2-year perennial forage (IA, OH1, and OH2) and increased when adding a 3-year perennial forage (MD, WI1, and WI2). The yield penalty was stronger for lower-value, mixed perennial forages (\$179 Mg^{-1} present at OH1 and OH2) than for higher-value alfalfa (*Medicago sativa* L., \$235 Mg^{-1}, present at IA, MD, WI1, and WI2).

Assessing the impact of rotational complexity using output highlights the trade-offs of including perennial or cover crops in a rotation because of their reduced contribution to rotation-level output. Perennial crops had lower output in their establishment year, which represents an opportunity cost compared with rotations that only contained annual crops. Cover crops, which are not harvested, do not directly contribute to output and have been shown to have mixed impacts on yields of annual crops.[38,39] However, including perennial forages or cover crops may provide ecological benefits that may enhance the output of other crops, such as through enhanced soil carbon inputs and improved aggregate stability[40] that were not accounted for directly in our models. Although some positive effects on agroecosystem properties (e.g., greater yields from increasing soil organic carbon, Vendig et al.[41]) were accounted for intrinsically via reduced risk and increased yields of crops over time, the magnitude of increased ecosystem services would be expected to vary depending on the diversification strategy, management practices, and climatic and edaphic environment. Based on previous research, we would expect rotational complexity to increase or stabilize yields of individual crops and complete rotations over time.[11,13,15,16]

Diversifying crop rotations is a risk-mitigation strategy

We found partial support for our hypothesis that the portfolio effect of complex rotations leads to more beneficial effects on

(colored by diversification strategy) medians of posterior parameter estimates from 32,000 Markov Chain Monte Carlo (MCMC) iterations. Error bars represent the 95% highest probability density interval (HPDI). The panel for complete rotations has larger axis scales than the individual crop panels, which have identical scales. Diversification strategies are described in Table 1. Values are shown in Table S4.

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Table 2. Model coefficients summarized by diversification strategy for complete rotation and component crops

Diversification strategy	RCI effect ($ ha^{-1})			EI:RCI effect ($ ha^{-1} RCI^{-1} $ EI^{-1})		
	Median	Lower 95% HPDI	Upper 95% HPDI	Median	Lower 95% HPDI	Upper 95% HPDI
Complete rotation						
Population average	−15	−62	32	−0.11	−0.16	−0.06
Annual	110	−30	209	−0.14	−0.22	0.00
Cover	−22	−169	121	−0.07	−0.21	0.08
Annual and cover	−29	−248	182	−0.04	−0.23	0.22
Annual and perennial	−133	−427	199	−0.41	−0.54	−0.08
Annual, cover, and perennial	−3	−70	262	−0.03	−0.14	0.08
Maize						
Population average	114	90	137	0.02	0.00	0.03
Annual	200	92	250	−0.01	−0.05	0.04
Cover	71	−13	154	0.02	−0.03	0.08
Annual and cover	79	−21	264	0.02	−0.03	0.09
Annual and perennial	105	70	152	0.01	−0.04	0.05
Annual, cover, and perennial	52	7	95	0.03	−0.02	0.08
Soybean						
Population average	75	57	92	0.02	0.00	0.03
Annual	128	102	154	0.01	−0.03	0.03
Annual and cover	46	2	127	0.02	−0.01	0.05
Annual, cover, and perennial	104	50	163	0.01	−0.03	0.05
Spring small grains						
Population average	47	−94	172	0.01	−0.11	0.11
Annual	−16	−75	47	0.03	−0.04	0.10
Annual, cover, and perennial	71	1	121	0.00	−0.10	0.08
Winter wheat						
Population average	4	−13	22	−0.00	−0.04	0.03
Cover	15	−30	81	0.03	−0.03	0.12
Annual and cover	2	−40	38	−0.01	−0.10	0.06
Annual, cover, and perennial	17	−9	49	−0.01	−0.06	0.03

Rotational complexity is represented by a continuous index, RCI. Growing conditions are represented by an environmental index, EI, which is the average output within a site-year, accounting for management differences. Diversification strategies are described in Table 1. The RCI effect describes how output changes with increasing rotational complexity under constant conditions. The EI:RCI effect describes how the RCI effect changes with growing conditions. Effects are considered significant if the 95% highest probability density interval (HPDI) is entirely above zero or below zero. Values <0.005 are shown as 0.00.

rotation-level output under poor growing conditions. Output losses were mitigated in complete rotations under poor growing conditions across sites, which reflected a reduction in downside risk consistent with the portfolio effect.[25] Reduction in downside risk was particularly pronounced in the four sites that diversified by adding perennial crops to annual crops (OH1, OH2, WI1, and WI2), even though overall effects on rotation-level output were mixed. More complex rotations combined crops with a greater variety of traits that enhanced the likelihood of performing well. The portfolio of crops faced different exposure to adverse growing conditions, and their traits allowed crops to acquire resources differently and respond differently to stressors.[27]

Although many studies refer to the portfolio or insurance effect in diversifying cropping systems, the reduction in downside risk (i.e., output loss) due to the portfolio effect is rarely quantified directly.[25] More commonly, studies make inferences about the portfolio effect based on individual crop or ecosystem responses to diversification under varying conditions.[11,13] Quantifying the portfolio effect of crop rotations directly requires assessing output on a rotation level. We found reductions in downside risk at the rotation level that were not apparent at the crop level. Understanding the behavior of component crops within a rotation then further allows farmers to select crops based on their desired level of output and risk. Our study is the first to directly quantify the portfolio effect across multiple long-term cropping systems experiments.

Our inferences about the portfolio effects from diverse rotations rely on an EI derived from output, as opposed to weather-based metrics. The advantage of an output-based EI is that it reflects the combined effects of weather and management variables that would be difficult to analyze directly. However, the output-based EI metric cannot discern how particular aspects of adverse weather influenced rotational complexity effects on output. Other studies have incorporated weather

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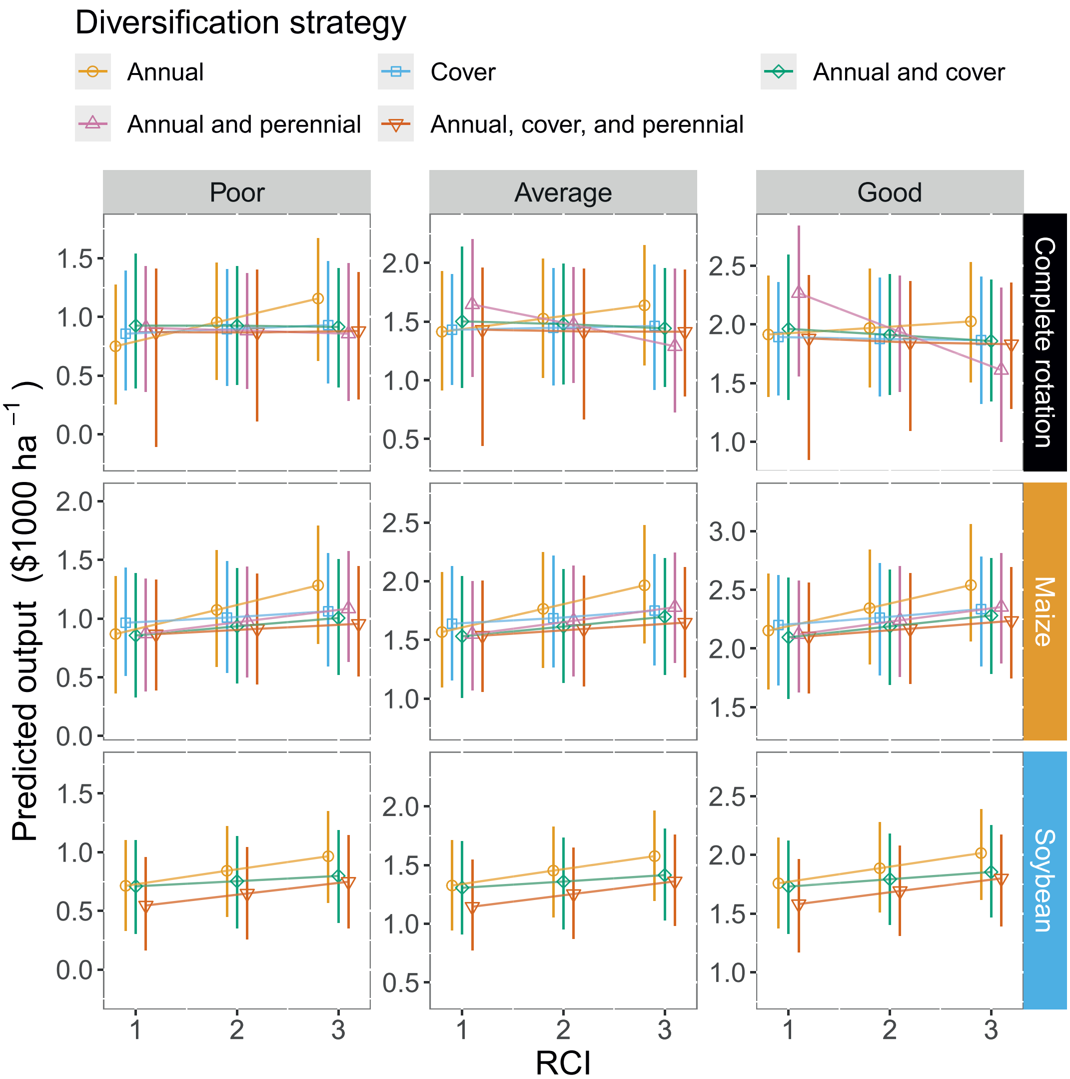

Figure 4. Adjusted predicted output under various growing conditions by diversification strategy

Points represent median values of adjusted predicted output from 1,000 posterior parameter draws for three levels on the rotational complexity index (RCI). Error bars represent the 95% HPDIs of these predictions. Predicted output includes variance due to grouping variables (site, block, and management subgroup) and residual variance. Predicted output was adjusted to correct for uneven distribution of sites across diversification strategies (Table 1) by subtracting the observation-specific environmental index (EI) term and adding a common EI term based on growing conditions. Poor, average, and good growing conditions are represented by the 10th, 50th, and 90th percentile EI of the entire dataset, respectively. The y- axes are the same length so that lines are comparable across panels but centered at different values to show subtle trends. Figure S1 shows adjusted predicted output for spring small grains and winter wheat. Error bars represent the 95% highest probability density intervals (HPDIs) of these predictions.

variables directly. For example, Marini et al.[15] examined precipitation and temperature effects on rotational complexity and found that crop rotations reduced yield losses of small grains from extreme precipitation and temperature compared with continuous monocultures, particularly under dry conditions.

Output on a dollar basis provides only a partial assessment

Quantifying rotation-level output as dollars per hectare was a reasonable metric for our dataset because it provided a relevant reference for farmers and made no assumption about crop end-uses, which varied across the cropping systems represented in each site. However, other approaches to calculating rotation-level output could lead to different conclusions about the benefits of rotational complexity. For example, we found that the addition of alfalfa to maize and soybean rotations increased rotation-level output at WI1. However, Sanford et al.[13] found the opposite trend at WI1 when quantifying rotation-level output as human-consumable calories from milk and soybean oil. With output quantified as calories, alfalfa was valued less than corn or soybean because of differences in calories per Mg. Quantifying output as dollars per hectare increased the relative value of alfalfa and also circumvented the issue of interpreting output from products with differing nutritional quality (e.g., milk and soybean oil).

While our results were reported as output on a dollar basis, our purpose was to assess yield responses, not economic performance of rotations. Evaluating economic performance of rotations requires information about production costs, price variation, government subsidies, and other information tailored to each location and production system. Such information was beyond the scope of this study. Several DRIVES sites have compared economic performance of crops or complete rotations among cropping systems at their individual sites.[42–47] In some cases, net returns were reduced in more complex rotations due to addition of lower-value crops that reduced gross returns.[40] In other cases, net returns increased in more complex rotations due to higher yields of more profitable crops[46] (higher gross returns) or lower production costs offsetting lower gross returns.[42] However, those outcomes depended on which inputs were included in analyses. For example, several sites found that more intensively managed simple rotations would be costlier without government support.[42,43] Other important factors that contributed to whether input costs changed the net returns of rotations were location,[43,46] labor costs,[42,45] and organic price premiums.[43,45]

Net returns of diverse rotations can be enhanced by ecological benefits that reduce input costs. Increased rotational complexity has been shown to reduce weed pressure and thus the amount of pesticides required.[42,48] Legumes in rotations have been shown to reduce the amount of synthetic fertilizer required to maintain yields,[42,44] although sourcing N from legume cover crops is not consistently economical for producers.[47] In their experiment, Davis et al.[44] found that crop yield, weed suppression, and economic performance were similar across three rotations, but the external inputs were greater in the simple systems with worse environmental impacts. Ecosystem services that reduce input costs have been shown to accrue over time in both organic and non-organic cropping systems, especially with perennial forages.[13,43,45]

Impact and adoption of diverse rotations

Despite the predominance of simplified crop rotations in North American agriculture,[49] our results indicate the potential for increasing or maintaining output at the crop level with minimal trade-offs at the rotation level by increasing crop-rotational complexity. Our approach of quantifying rotation-level output on a dollar basis amplified the effect of highly productive crops and market valuation. Market valuation is shaped by government policies that incentivize additional demand for these crops, such as direct and indirect subsidies for maize-based biofuels and confined animal feedlot operations.[50,51] Alternative "metrics of success" for crop-rotational complexity such as economic performance using net returns, nutritive value of diets, impact on environmental quality, and the degree of non-renewable inputs required may not support the status quo favoring simple rotations (i.e., one or two crops).[18,22] Quantifying output on a dollar basis illustrates some possible trade-offs of more complex rotations, particularly in regard to the establishment year for perennial forages, which tended to lead to mixed results for rotation-level output. When considering adoption of more diverse rotations, these trade-offs need to be considered in the absence of other structural and policy changes. Although we chose a conservative metric that is biased toward the predominant agricultural system, our results have demonstrated that output of simplified rotations can fall below output from more complex rotations, especially under poor growing conditions. This finding corresponds with the reliance of simplified cropping systems on publicly subsidized crop insurance in the United States.[52]

Increasing rotational complexity faces barriers to voluntary adoption. More diverse rotations increase management complexity, require additional knowledge and understanding of new crops and additional commercial relationships, and, possibly, the need for new equipment.[53] Additionally, producers face the economic, social, and psychological hurdles of growing less-valuable crops on premium land.[54] Limited availability of local markets for crops such as small grains and perennial forages further inhibit farmers from growing and harvesting these crops.[55]

However, many stakeholders besides the producer are involved with adoption of more complex crop rotations. Cultivating networks of stakeholders that support diversification is one pathway to greater adoption, especially in ways that provide a sense of community and shared mission. Broad strategies to support diversification range from breeding for diverse rotations[56] to changing institutions to remove economic barriers.[57] Scaling up adoption of complex crop rotations requires new organizational forms (e.g., contractual arrangements and partnerships) and consistent funding through the formation of value chains that align with diversification (e.g., legal frameworks and financial incentives).[58] Interest in ecosystem service or carbon markets can be leveraged to support diversification efforts,[59] although the lack of consensus in environmental accounting standards is a barrier.[60] Increasing adoption of more complex rotations also requires creation of policies that enable change and transformation of policies that currently act as barriers.[61,62] While we showed that more complex rotations had mixed results on rotation-level output using a conservative approach, accounting for cost of production will likely improve economic attractiveness of lower-value crops and thus their rotation-level outcomes, as would accounting for the environmental costs of the high inputs required for maintaining yields of simplified rotations. Additionally, higher market valuation that increases prices for perennial crops (i.e., as bioenergy or carbon capture) would further improve the output-based outcomes of more complex rotations.

EXPERIMENTAL PROCEDURES

Resource availability

Lead contact

Further information and requests for resources should be directed to and will be fulfilled by the lead contact, K. Ann Bybee-Finley (ann.bybee-finley@ncsu.edu).

Materials availability

This study did not generate new unique materials.

Data and code availability

Any additional information required to reanalyze the data reported in this paper is available from the lead contact upon request. The crop-yield data used in this study cannot be deposited in a public repository because collaborating sites have not provided permission to publish their data at this time. Code and limited data are available at https://doi.org/10.15482/USDA.ADC/25943899.v1.[63]

Dataset description

Crop yield and experiment design metadata were obtained from 20 long-term cropping systems experiments across North America and organized into a database (Figure 5 and Tables S1–S3). All experiments had at least three

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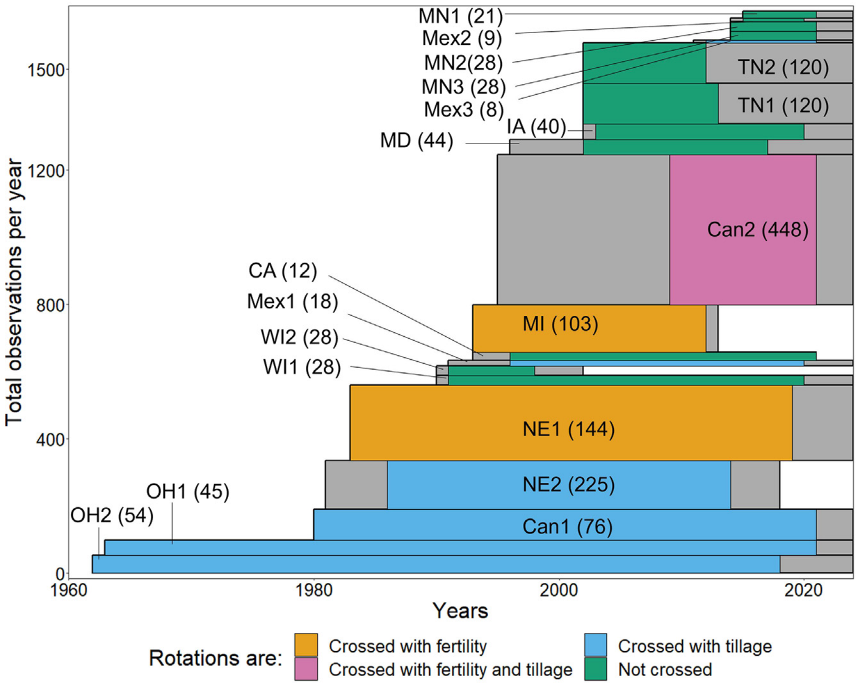

Figure 5. Timeline and size of the DRIVES dataset used in analysis

Lengths of rectangles represent years of data at each of the 20 experiments and heights of rectangles represent the median number of observations per year, reported in parentheses. Colored areas describe additional treatments to crop rotations, if any. Gray-shaded areas indicate years that data were unavailable or excluded from analysis. Additional details about each experiment are presented in Tables S1–S3 and Note S3.

replications except for the Mex1 and Mex3 sites, which had two replications. All experiments were randomized complete block designs except for the CA site, which was completely randomized. In these studies, crop rotations occurred in the same space over time and were partitioned into phases. We define a phase as the time period between planting one harvested crop to the next. We selected experiments in which all rotation phases were present every year so that all harvested crops in a rotation were grown under the same weather conditions (see Note S3 for more details).

Crop-yield data consisted of marketable crop fractions (i.e., grain or forage biomass) measured in dry yield per hectare and summed across multiple harvests per season, when applicable. Straw was included as a component of small grain yield when harvested (5 of 16 sites), but not when it was left in the field as residue. For some sites, data were not available for certain years, or, in other instances, not enough data were available following significant changes to cropping system treatments (Figure 5 and Note S3). Low yields from non-error circumstances were included, as these data potentially reflected outcomes from difficult growing conditions.

We used yield data to quantify outputs for complete rotations and for individual crops within rotations. Four individual crops had sufficient data for analysis: maize, soybean, spring small grains, and winter wheat. The spring small grains category included barley, oats, spring wheat, and triticale harvested the same year they were planted. Data were filtered to ensure that individual crop yields were represented in at least two rotations within each site-year. The sample sizes were 15,438 observations from 406 site-years for complete rotations, 14,744 observations from 420 site-years for maize, 9,435 observations from 174 site-years for soybean, 877 observations from 76 site-years for spring small grains, and 2,123 observations from 65 site-years for winter wheat.

For rotation-level analysis, non-maize continuous monocultures were removed so that effects of rotational complexity could be compared from a common baseline. Continuous maize monocultures were present in 14 out of 19 sites used for rotation-level analysis. At the five sites without continuous maize (IA, MD, and MN1–3), the simplest rotation was alternating maize and soybean (with cover crops at MD). Maize was only absent from one site (CA), which was used soley in the winter wheat model.

To prepare for the rotation-level analysis, phases with missing yield data were imputed to maximize the number of site-years and make best use of available data. When possible, missing yields were imputed as the average of non-missing experimental replicates from the same rotation phase, management treatment, and year. Yields imputed from non-missing replicates were present within 1.6% of rotation-level observations. When all experimental replicates were missing, yields were imputed using generalized additive models (GAMs) with year as a smoothing variable, fit with data from the relevant site. The GAMs were implemented using the R package "mgcv."[64] Yields imputed with GAMs were present within 2.1% of rotation-level observations.

To analyze yield at the rotation level, we must convert dry yield on a weight basis to a common unit that can be combined among crops. Dry yields were converted to output on a dollar basis ($ ha^{-1}). To do this, we used United States national average crop price data from the United States Department of Agriculture National Agricultural Statistics Service (USDA-NASS).[32] Yields for each crop were converted to output by multiplying a price coefficient that remained constant across all years. The price coefficient was calculated from the average market value from the years 1991–2019, which was the longest interval available that included all crops. Market values were adjusted for inflation and converted to a dry-yield basis using standard moisture for each crop so that prices were in units of dollars per kilogram of crop dry weight (Note S1). Crop yields reported at standard moisture were also scaled to units of dry weight before converting to output.

The reason we opted for a single price coefficient, instead of using historical prices from the years that crops were produced, was that doing so would introduce another source of variability that would complicate our efforts to understand the effects of rotational complexity on productivity. Price variability could interfere with conclusions about relative output of different rotations if crops were negatively correlated. However, historical prices were positively correlated across all crops (Figure S11), which means that their relative value remained similar over time. We performed a sensitivity analysis to assess how the choice of price coefficient influenced model outcomes for complete rotations. Inferences about effects of rotational complexity did not substantially change when price coefficients varied over their historical range (Note S2).

Output at the rotation level was quantified by summing dollar outputs from all marketable crops (i.e., excluding cover crops) and dividing by the length of the rotation in years. Thus, rotation-level output is the average output per year of all crops under common conditions, weighted by their inflation-adjusted average market value. Although two sites were managed organically (Table S2), only non-organic crop prices were used, since our analysis did not compare organic and non-organic treatments at any site. For individual crops, modeling output on a dollar basis is equivalent to modeling yield on a weight basis (except for output from adding grain and straw from small grain crops). Individual crop yields were converted to dollar output for consistency of reporting results.

Temporal detrending

We expected long-term crop data to show a trend of increasing yield over time due to breeding and other technological advancements.[65] To correct for this, we detrended crop yields with a simple linear regression of yield versus year. Crop yields were combined across sites to capture broad-scale trends (Note S5). Some crops were grouped into larger categories for detrending. Winter wheat and spring small grains were combined into a small grains category.

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Alfalfa and non-alfalfa hay were combined into a perennial forages category. Crop and rotation-level output was calculated using detrended yields.

Rotation and environmental indices

Treating rotational complexity as a continuous metric provides a straightforward method to describe a broad range of crop rotations with a single statistical predictor. However, no metric adequately identifies all aspects of rotational complexity that are important for yield or other biophysical responses. In a preliminary analysis, we evaluated several metrics that reflect different aspects of crop rotations. The inverse Simpson's diversity index (DI) is one of several metrics from community ecology that has been applied to crop rotations.[12] The DI value reflects the number of distinct crops in a rotation (species richness) and their evenness over time. The RCI, developed by Bowles et al.,[11] is calculated from the number of unique crops in a rotation (including cover crops) and the number of years in a full rotation cycle (Equation 1). Species mixtures, such as those used in perennial forages and annual cover crops, are treated as a single crop for calculating DI and RCI. We also considered a metric describing the proportion of time that crop cover is present in a rotation (proportion cover), as well as the DI and RCI multiplied by the proportion cover to penalize periods of bare soil. Based on preliminary comparisons, RCI proved the best descriptor of rotational complexity in our dataset, which often included perennial crops in higher-diversity treatments. The evenness term in the DI effectively penalizes perennial crops in a rotation because perennials are often grown for multiple years, thereby reducing evenness compared to rotations with only annual crops. Length and species richness are fundamental attributes of crop rotations that can be calculated for any rotation without subjective assumptions.

We calculated RCI as follows:

$$\mathrm{RCI} = \sqrt{r * l}, \qquad \text{(Equation 1)}$$

where r is the number of unique crop species (richness), including cover crops, and l is the length of a full rotation cycle, in years.

We used an EI to represent growing conditions (Equation 2). Originally developed for plant breeding,[31] EI is the average output (y), measured for (n) observations across all rotations in a given year (t) and management subgroup within a site (g):

$$\mathrm{EI}_{gt} = \frac{1}{n_{gt}} \sum_{i=1}^{n_{gt}} y_i. \qquad \text{(Equation 2)}$$

The EI was calculated within a given site and management subgroup, so that annual variation in EI reflects a combination of changing environmental conditions (e.g., weather) and management outcomes (e.g., improved weed management over time, accrual of soil organic matter). Thus, the deviation between output and EI reflects differences among crop rotations, and no other management practices. Separate EIs were calculated for complete rotations, maize, soybean, spring small grains, and winter wheat. Lower values of EI represent poorer growing conditions.

Analysis

Data were analyzed using R version 4.1.1.[66] Bayesian multilevel models were used to quantify how rotational complexity influenced output under varying growing conditions. Bayesian methods provide more robust estimates of parameter values and uncertainty than frequentist methods; they are also known to provide a more accurate quantification of uncertainty, reducing the risk that the model outputs will be overly optimistic about their uncertainty reports.[67]

Separate linear regression models (Equations 3 and 4) were fit to analyze output for complete rotations, maize, soybean, spring small grains, and winter wheat. The likelihood function is a non-standard student t distribution,

$$y_x \sim \text{student } t\left(\mu_x, \sigma^2, \nu\right), \qquad \text{(Equation 3)}$$

where y_x is the output for an individual experimental unit x in a given year (the index x represents the unique unit-year pair). Deviation from the expected value (μ_x) is σ^2. The degrees of freedom parameter (ν) is an integer that governs the weight (thickness) of the tails. The lower ν is, the heavier the tails. The student t distribution converges to a Gaussian distribution as ν tends to infinity. The student t distribution is better for describing data with outliers, as was the case for our dataset. It is a conservative choice that enhances our model's ability to avoid under-reporting predictive uncertainty.

The expected value for output was obtained from a linear model with varying intercepts and slopes:

$$\begin{aligned}\mu_x &= a + a_{site_x} + a_{mgmt_x} + a_{replicate_x} + b\mathrm{EI}_x \\ &+ \left(c + c_{mgmt_x}\right)\mathrm{RCI}_x + \left(d + d_{mgmt_x}\right)\mathrm{EI}_x\mathrm{RCI}_x.\end{aligned} \qquad \text{(Equation 4)}$$

Coefficient a describes the linear intercept. The model includes a global grand mean intercept (a), varying group-level intercepts for experimental sites (*site*), management subgroups within sites (*mgmt*), and replicate within sites (*replicate*) (Tables S1 and S3). Coefficient b describes the effect of EI on output. Because of how EI is calculated (Equation 2), the value of b will be close to 1. Adding group-level terms to b does not improve the model, as these terms are statistically indistinguishable from zero, serving only to reduce the model's predictive power. Coefficients c and d describe the main effect RCI and the interactive effect of RCI and EI, respectively. Both coefficients include a group-level effect for management subgroups within sites. To ease model interpretation, continuous predictors and response variables were centered at zero.

Bayesian models were implemented in Stan v.2.21.0[68] via the R package "brms,"[69–71] using the Hamilton Monte Carlo algorithm to approximate Bayesian posterior distributions. Model fits used four parallel chains of 12,000 iterations (including 4,000 burn-in iterations), giving a total of 32,000 post-warm-up iterations per model. Without strong a priori knowledge about the regression coefficients and the statistical noise variance σ^2, prior distributions were set to be weakly informative. Population-level regression coefficients (a, b, c, d) were specified with normal priors with a mean of zero and variance set to an appropriate scale for the data (Note S6). Group-level coefficients were specified as normal distributions centered at zero with hyperparameters for standard deviation. Hyperparameters for group-level standard deviation

($\sigma_{a\ site}, \sigma_{a\ mgmt}, \sigma_{a\ replicate}, \sigma_c, \sigma_d$) and the parameter for population-level standard deviation (σ in Equation 3) were specified as half non-standard student t priors, as recommended by Gelman[72] (Note S6). The degrees of freedom parameters (ν) were specified with a gamma distribution, which is a common weakly informative prior for skewness in student t distributions.[73] The model also contains parameters for the three-way correlation among coefficients nested within management subgroup ($a_{mgmt}, c_{mgmt}, d_{mgmt}$), which is specified with a Lewandowski, Kurowicka, and Joe (LKJ) prior with a shape parameter of 2. The LKJ distribution generates random correlation matrices, which are used with the Cholesky factor to generate covariance matrices.[74]

Model evaluation and reporting

Model fits were evaluated based on sampling efficacy in split chains, successful chain convergence, and posterior predictive checks (Note S7, Table S7, and Figures S15–S19). Models were considered to have adequate sample size if rank-normalized effective sample size (bulk ESS) and effective sample sizes at the 5% and 95% quantiles (tail ESS) were greater than 400 for all model parameters.[75] Models were judged as sufficiently converged if all parameters had split-$\widehat{R}$ (sometimes referred to as Rhat) convergence statistics between 1.00 and 1.01 and rank histograms showed uniform distribution of parameter draws across chains.[75,76] Effective sample sizes and $\widehat{R}$ values were obtained through the "brms" package.[69] Rank histograms were generated with the "bayesplot" package.[77] Posterior predictive checks were used to calculate in-sample empirical coverage probability, which indicates how well the model predicted the data used to fit the model.

Bayesian analysis provides probability (posterior) distributions for all model terms, including posterior predictive distributions, which are obtained by mixing the model's student t distribution with the regression coefficients and variance parameter's posterior distributions. To summarize results, we presented medians and 95% highest probability density intervals (HPDIs) for each scalar variable. Analogous to confidence intervals in frequentist statistics, HPDIs are Bayesian credibility intervals containing a parameter's values with posterior probability equal to 95%; the use of "highest density" means that those intervals are the shortest possible. A 95% HPDI is useful for hypothesis testing because it indicates whether a given parameter is significantly above or below zero based on an $\alpha = 0.05$. Unless stated otherwise, effects are reported as above or below zero at a 95% Bayesian credibility level. For instance, we considered the effect of rotational complexity on output to be positive if the 95% HPDI for coefficient *c* (Equation 4) was entirely above zero. Occasionally, we reported probabilities below the 95% significance level to describe effects that were apparent, but not statistically significant. For example, if the widest HPDI above zero was 70%, we would report a 70% probability of a positive outcome.

Predicting output by diversification strategy

Model posterior estimates were used to predict how rotational complexity influenced output under various growing conditions while accounting for inherent differences among sites and management groups. First, 1,000 random samples were drawn from the 32,000 generated sets of posterior parameter estimates from the Markov Chain Monte Carlo (MCMC). For each set of posterior parameters, we simulated a dataset representing all grouping levels (i.e., site, management subgroups, and block), as well as residual error in the model. Predictions were made for an RCI of 1, 2, and 3 over varying growing conditions, represented by EI. The EI was calculated separately within each management subgroup as the 10^{th}, 50^{th}, and 90^{th} percentile, to represent poor, average, and good conditions.

We aggregated predictions across all sites for the population-level average and for sites within a diversification strategy (Table 1). To correct for differences in output due to location and other management treatments, we took the predicted output and subtracted the product of the EI and the EI coefficient (*b* in Equation 4) within each sample iteration. Since EI is the average output within a management subgroup and year, this corrected value represents the deviation from average output due to rotational complexity and error terms. This deviation was then converted to absolute predicted output by adding a common EI value. The common EI value was the 10^{th}, 50^{th}, or 90^{th} percentile EI of the entire dataset used to fit the model.

Reporting site and population-level effects

The Bayesian regression model described in Equation 4 produces posterior estimates for coefficients *c* and *d* at the population level and at level of management subgroups within sites (*c* + *c_mgmt*). Population-level results (i.e., across sites) for coefficients *c* and *d* are reported per unit of RCI from the model output directly. Site-level results are obtained by aggregating coefficients for management subgroups within sites (Table S3). Site-level results exclude management subgroups with unrealistically low N addition—i.e., two out of eight subgroups at Can1 and one out of three subgroups at NE2. Coefficients are summarized as the median and 95% HPDI from 32,000 MCMC iterations. Positive or negative results are reported at the 95% Bayesian credibility level, unless stated otherwise.

Quantifying interactions between rotational complexity and fertility and tillage regimes

For a subset of sites, we examined specific management effects on output response to rotational complexity across the three EI conditions. Among the 20 sites, seven had management subgroups representing contrasting tillage treatments (including no-till, chisel-till, and moldboard plow) and three had management subgroups representing contrasting fertilizer treatments with varying rates and types of N (Figure 5 and Table S3). Here, low and high N rates refer to rates that are lower and higher than the recommended rate for the crop.

Because these N fertility and tillage treatments were coded as separate management subgroups in the model, we compared posterior estimates for group-level regression coefficients to assess how the effects of rotational complexity varied among management treatments. To do this, we performed pairwise contrasts on group-level regression coefficients for the main RCI effect and interactive EI:RCI effects. The difference between group-level coefficients was calculated within each of the 32,000 MCMC iterations. Pairs of groups were considered significantly different if the 95% HPDI of this difference was entirely above or below zero (i.e., 95% Bayesian credibility level). One site (Can2) had crossed N fertility and tillage treatments, and contrasts were made accordingly for each factor.

Effects of N fertility and tillage treatments were also visualized by predicting output for an RCI of 1, 2, and 3 under poor, average, and good conditions, defined as the 10^{th}, 50^{th}, and 90^{th} percentile EI within management subgroups. This is similar to our approach for visualizing average outcomes for all sites and sites grouped by diversification strategy, except that we did not correct for differences in performance among management subgroups. In this context, differences in the predicted output indicate actual differences in the productivity of N fertility and tillage treatments.

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.oneear.2024.07.008.

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AUTHOR CONTRIBUTIONS

K.A.B.-F., K.M., K.E.W., A.C.M.G., B.W., F.V., G.S., H.H.S., H.K., M.L., M.A.C., S.S., S.F., T.M.B., and V.R.S. conceptualized the research; K.A.B.-F., K.M., K.E.W., F.V., H.H.S., and T.M.B. developed methodology; K.A.B.-F., K.M., A.C.M.G., B.W., D.C.H., G.S., K.J., L.D., M.L., M.A.C., S.S., and S.F. curated data; K.A.B.-F., K.M., and F.V. conducted formal analysis; K.A.B.-F. and K.M. developed visualizations and software; K.A.B.-F., K.M., H.H.S., and T.M.B. wrote the original draft of the manuscript; K.A.B.-F., K.M., K.E.W., A.C.M.G., A.G.y.G., D.C.H., E.H., F.V., G.J., G.S., H.H.S., H.K., J.S., M.D.M., M.R.S., M.L., M.A.C., N.V., S.S., S.F., T.M.B., A.A.C., and V.R.S. reviewed and edited the manuscript; K.E.W., A.C.M.G., F.V., H.H.S., L.D., M.A.C., S.S., and T.M.B. acquired funding; G.J., H.H.S., V.J., M.D.M., and T.M.B. provided resources; K.A.B.-F., F.V., H.H.S., and M.A.C. administered the project; and F.V., H.H.S., and T.M.B. provided supervision.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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