The impact of agricultural landscape diversification on U.S. crop production

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Abstract: The last century has seen a dramatic simplification of global landscapes, driven largely by the expansion and intensification of agriculture. Landscape simplification has known negative impacts on ecosystem health and function; however, less is known about how landscape simplification affects agricultural production. There is mounting *field-scale* evidence that simplification can reduce agricultural production by eroding the ecosystem processes on which agricultural systems depend; however, many of these processes emerge not at the field scale, but from complex interactions between land use, biophysical context, and human activity at the *landscape scale*. This research uses hierarchical Bayesian models to estimate the relationship between landscape-scale agricultural diversity and the yields of corn, soy, and winter wheat in the coterminous United States. We find that the yields of corn and winter wheat increase by as much as 20% in highly diversified agricultural systems. Our findings also indicate that (1) crop production is more responsive to the number of distinct crop types cultivated on a landscape than their cultivated extent and that (2) increasing diversity in agricultural systems that are already diverse brings the highest yield gains. Our models provide strong evidence at national and regional scales that agricultural diversification—an intervention with known ecosystem benefits—can increase crop production.

Highlights:

- The yields of corn and winter wheat increase by as much as 20% in highly diversified agricultural systems, while soy yields increase by nearly 5%.
- Crop production is more responsive to the number of agricultural land use categories in a system than the relative cultivated extent of each category.
- Increasing agricultural diversity in systems that are already diverse brings the highest yield gains.

Keywords: Diversity, crop production, United States

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1.0 INTRODUCTION

The last century has seen a dramatic simplification of global landscapes, driven largely by the expansion and intensification of agriculture (Aguilar et al., 2015; Khoury et al., 2016; Landis, 2017). Agriculture now covers one-third of global land, making it the most significant "engineered ecosystem" on the planet (Zhang et al., 2007). In the U.S., agriculture accounts for over 50 percent of total land area (Figure 1) – and over half of this land is cultivated with corn, soy, or wheat (Bigelow & Burchers, 2012). Simplified agricultural landscapes with low levels of natural habitat and plant diversity are optimized for crop production (Meehan et al., 2011, Grab et al. 2018); however, they are also associated with soil degradation, loss of habitat, reductions in water quality, and loss of species diversity (Bommarco, Kleijn, & Potts, 2013; Hendrickx et al., 2007; Landis, 2017; McDaniel, Tiemann, & Grandy, 2014; Tiemann, Grandy, Atkinson, Marin-Spiotta, & McDaniel, 2015; Tscharntke et al., 2012). These negative environmental impacts in turn erode the ecosystem processes essential to crop production such as pollination, pest management, water retention, and nutrient supply (Swift et al., 2004; Zhang et al., 2007). This implies that over time agriculturally-driven landscape simplification may diminish agricultural productivity.

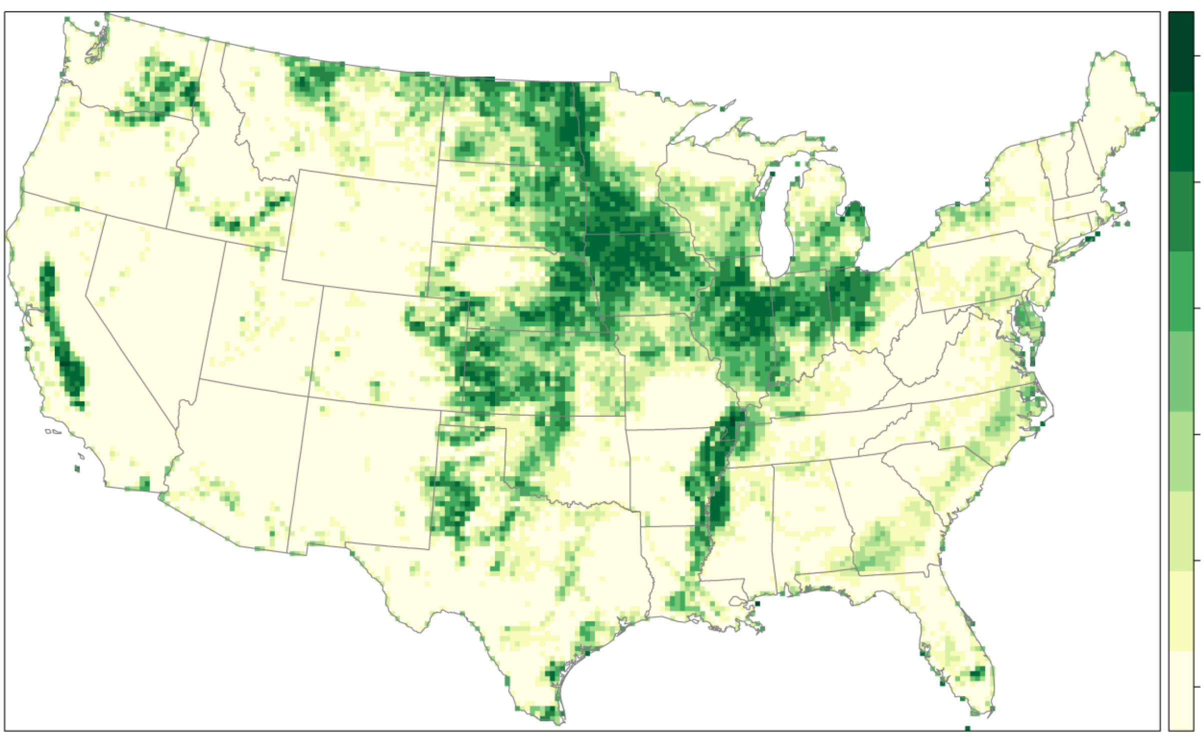

Figure 1: The proportion of agricultural land use across the U.S. as indicated by the USDA CropScape dataset (2017). Dark green indicates a higher intensity of agricultural land use.

An axiom of ecology and sustainability science is that diversity increases the health and function of complex systems (Bommarco et al., 2013; Khoury et al., 2016; Walker et al., 2004). Evidence from hundreds of experiments confirms that diversity, in and of itself, is essential to ecosystem productivity (Cardinale et al., 2012, 2006; Hooper et al., 2012; Loreau et al., 2001; Tilman et al., 2014, 2012). Despite being inextricably linked to ecological systems, agricultural systems are often purposefully managed to *reduce* species diversity to increase harvestable yields. Farmers, who play a central role in the selection of which species are present on a landscape, are influenced by policies and institutions endorsing specialization as a tool to increase agricultural productivity (Nassaur, 2010; Roesch-McNally, Arbuckle, & Tyndall, 2018; Yoshida, Flint, & Dolan, 2018). Whether this economic assumption aligns with biological reality is highly contested (Cassman, 1999; Davis et al., 2012; Kremen & Miles, 2012; Reiss & Drinkwater, 2018; Virginia et al., 2018).

Field-scale experiments suggest that—as in ecological systems—diversity can actually *increase* agricultural production (Li et al., 2009; Ojha & Dimov, 2017; Smith, Gross, & Robertson, 2008; Tscharntke et al., 2005). Smith and colleagues (2008) found that corn yield increases were 100 percent higher in diverse agricultural systems as compared to monoculture systems. Pywell et al. (2015) and more recently Schulte et al. (2017) found that transforming even a small percentage of agricultural land to wildlife habitat maintained or improved yields. Several papers have found that crop diversity is associated with reduced yield volatility over time (Abson, Fraser, & Benton, 2013; Di Falco & Perrings, 2005; Weigel, Koellner, Poppenborg, & Bogner, 2018). Research suggests that these yield improvements are driven by the positive impact of diversification on the ecosystem services essential to crop production, including pest management (Bommarco et al., 2013; Chaplin-Kramer et al., 2011; Gardiner et al., 2009), soil health (McDaniel et al., 2014; Tiemann et al., 2015), and pollinator diversity (Schulte et al., 2017; Tscharntke et al., 2005).

Almost all of the existing evidence linking diversity to increased agricultural production is at the field-scale; however, many of the ecological processes on which agricultural systems depend emerge not at the field-scale, but from complex interactions between land use, biophysical context, and human activity at the *landscape scale*. Landscape composition and configuration have been shown to affect many of the ecosystem services essential to agriculture, such as water quantity and quality, pollination, pest regulation, carbon storage, and climate management (Li et al., 2009; Swinton, Lupi, Robertson, & Hamilton, 2007). In addition, many ecosystem services essential to agriculture such as pollinator movement and water flow are generated far from the agricultural fields that benefit from them. Therefore, field-scale efforts to diversify may be negated by landscape simplification and conversely, landscape-scale diversification may benefit localized monoculture systems (Tscharntke et al., 2005). For these reasons and the mounting evidence linking field-scale diversification to increased ecosystem services and agricultural productivity, we hypothesize that landscapes with higher levels of agricultural diversity will support more productive agricultural systems.

As agriculture becomes the most widespread use of land on Earth, there is a critical need to determine how and why agriculturally-driven landscape change affects agricultural production. This research uses Bayesian hierarchical modeling to estimate the relationship between agricultural diversity and the yields of corn, soy, and winter wheat in counties across the coterminous United States while controlling for seasonal climate, spatiotemporal dependencies, and regional factors known to influence yield. Our results indicate that agricultural diversity is associated with increased agricultural productivity and that it is primarily the number of agricultural land use categories, rather than their relative cultivated extent, that drive these yield gains. Regional variability in our models, however, highlights the continued importance of local and regional analyses to assess the complex assemblage of socio-ecological factors that mediate the diversity-productivity relationship across space and time.

2.0 METHODS

2.1 Data

The county-season is the smallest spatiotemporal unit at which public yield data is available nationally (USDA NASS, 2019); however, land use and weather data are available at much higher spatiotemporal resolutions. To resolve this scalar mismatch and preserve as much information as possible, we constructed county-scale indicators of cumulative seasonal weather exposure from gridded daily temperature and precipitation data and computed three indicators of county-scale agricultural diversity from annual 30 meter land use data. We extracted gridded land use and weather data to the county scale and merged this data with county-level yield estimates for corn, soy, and winter wheat for all counties in the conterminous U.S. (n=3108) from 2010 to 2016. We focus on corn, soy, and winter wheat because of their importance to the global economy and their prevalence on U.S. agricultural landscapes. Since the 1960s, harvested soy and corn acreage has increased by 76 percent (74 million acres), today covering about 90 million and 89 million acres respectively (Bigelow & Borchers, 2017). Wheat – including winter, durum, and spring wheat – comprises the third largest acreage in the U.S. at 46 million acres (Ash et al., 2018). Together, these crops cover more than 50% of cultivated land in the U.S.

Agricultural production is influenced by many factors other than land use, the most important of which is weather. To control for the impact of weather on crop production, we computed the average county-level temperature and precipitation for each day within a crop's spatially varying growing season (Ramankutty, Evan, Monfreda, & Foley, 2008) from four-kilometer gridded daily weather data provided by the PRISM Climate Group. From this daily data, we computed three indicators of seasonal weather: growing degree days (GDDs), stress degree days (SDDs), and total precipitation (TP). GDDs measure the accumulated degrees Celsius within a crop-specific temperature range in which a crop's growth rate increases (Miller et al., 2001). The tolerance range for corn and soy is 10–30^{o} C and 0-30^{o} C for winter wheat (Mesonet, 2017; NDAWN, 2017). To model the negative effects of extreme temperature on crop production (Lobell et al., 2013) we included SDDs, which are the total accumulated degrees Celsius above the maximum GDD temperature threshold. To control for the impact of water availability on yields, we also computed the TP or the cumulative sum of precipitation in millimeters throughout the growing season.

We used the USDA NASS Cropland Data Layer (CDL) as our indicator of land use. This dataset classifies land use at a 30-meter resolution nationwide from 2008 to 2017 using satellite imagery and extensive ground truth data. Using this data, we computed three county-scale indicators of agricultural diversity: the Shannon Diversity Index, the Simpson Diversity Index, and Richness. The Shannon Diversity Index (SDI) is a widely-used index of diversity that measures the proportional abundance of each land use category in a given region (Aguilar et al., 2015; Gustafson, 1998; Turner, 1990). It incorporates both the number of land use categories and their relative evenness on the landscape. The Simpson Diversity Index (SIDI) measures the probability that two pixels selected at random belong to different land use categories. The SIDI gives more weight than the SDI to common land use categories, i.e. rare land use categories will have a smaller effect on SIDI than SDI. We also computed richness (RICH), or the number of unique land use categories in a county. We extracted each index to the county-scale from the 100+ agricultural land use categories included in the CDL (see the SI Appendix for the full list of categories). Each index varies significantly across space, with the Midwestern U.S. generally exhibiting lower diversity than the Southern and Western U.S. (Figure 2). By running our models with three commonly-used indices of diversity, we can both test the sensitivity of our results to different operationalizations of diversity and assess the extent to which different facets of diversity, e.g. abundance or relative extent, affect yields. We include two additional spatially- and temporally-varying controls. The first is an indicator of the percent of irrigated land in a county extracted from the 250-meter gridded MiRAD dataset (Pervez & Brown, 2010). The second is an indicator of the prevalence and importance of a crop to a county's agricultural system, calculated as percent of agricultural acreage cultivated with the crop of interest.

Table 1: An overview of agricultural diversity indicators.

Index	Formula	Definition and advantages
Shannon Diversity Index (SDI)	$SDI = -\sum_{i=1}^{k} p_i \log(p_i)$	A measure of the abundance and evenness of land use categories. This index is sensitive to rare land use categories. Typical values are between 1.5 and 3.
Simpson Diversity Index (SIDI)	$SIDI = \frac{\sum n(n-1)}{N(N-1)}$	A measure of the abundance and evenness of land use categories. This index is *not* sensitive to rare land use categories. Values range from 0 to 1.
Richness (RICH)	Number of discrete land use types	A measure of the abundance of land use categories.

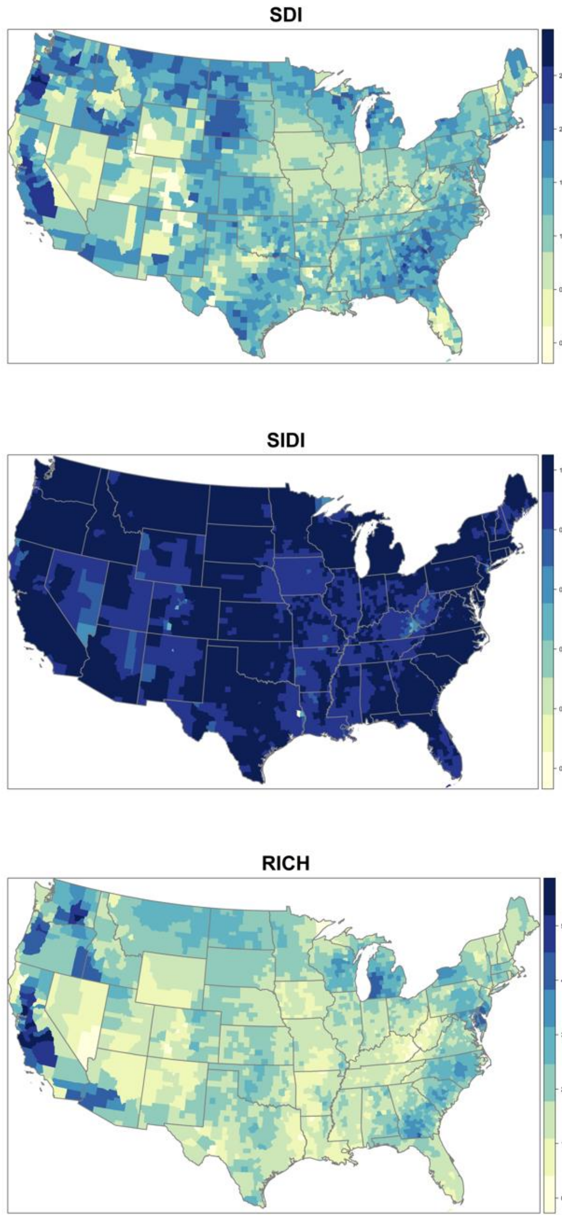

Figure 2: Variations in agricultural diversity as measured by the Shannon Diversity Index (SDI), the Simpson's Diversity Index (SIDI), and Richness (RICH) for counties in the conterminous U.S. in 2017.

2.2 Modeling

The quantitative modeling in this study builds on work employing advanced statistical regression of cross-sectional time-series data—also known as panel data—to investigate known nonlinearities in the relationship between crop production and seasonal weather (Blanc & Schlenker, 2017; Schlenker & Roberts, 2009). Agricultural production is strongly influenced by spatiotemporal context (Mendelsohn, & Massetti, 2017; Tack, Barkley, & Nalley, 2015); however, agro-climatic panel models typically employ frequentist statistics for which the incorporation of complex spatiotemporal dependency structures can be difficult and computationally expensive (Chatzopoulos & Lippert, 2015; Moore and Lobell, 2015). We leverage recent advances in Bayesian modeling

(Blangiardo & Cameletti, 2015; Mantovan & Secchi, 2010; Meehan & Gratton, 2016; Nelson & Burchfield, 2017) to control for the influence of spatiotemporal dependency in our estimation of the interactions between landscape, seasonal weather, and crop production. In addition to accounting for spatiotemporal dependencies which might otherwise bias our regression estimates, this approach has several advantages that are particularly relevant to our focus. First, it facilitates the estimation of known nonlinearities in the interactions between landscape, yield, and seasonal weather (Blanc & Schlenker, 2017; Butler & Huybers, 2015; Lobell et al., 2013; Schlenker & Roberts, 2009). Second, it controls for time-invariant spatially-varying factors (e.g. soil type, topography) and space-invariant temporally-varying factors (e.g. national policy changes, market variations) that influence yield, isolating yield variations driven by our variables of interest (Bivand, Gómez-Rubio, & Rue, 2015; Blangiardo & Cameletti, 2015; Meehan & Gratton, 2016). Third, this approach flexibly handles missing yield data by building model estimates using a combination of a specified likelihood function, specified prior probability distributions, and available data, providing multiple sources of information from which to build posterior effect estimates (Blangiardo & Cameletti, 2015).

We estimate a log-linear random-effects panel model that includes diversity (*D*), seasonal weather controls (*GDD, SDD, TP*), county-level spatial effects (*County*), and independent quadratic time trends for each region (*Time*) – identified using the Level III ecological regions provided by the US EPA (Figure 3) – to account for regionally-varying temporal changes that affect yield such as differences in technology adoption and management changes (Schlenker & Roberts, 2009).

$$\log(Yield)_{ijt} = f(D)_{it} + f(TP)_{it} + f(GDD)_{it} + f(SDD)_{it} + \\ Percent\_Irrigated_i + Percent\_Crop_{it} + f(County)_i + f(Time)_{jt}$$

where *i* indexes counties, *j* indexes regions, and *t* indexes year. County-level spatial effects (*County*) account for time-invariant factors associated with each county that influence yield including soil, topography, and non-dynamic sociocultural, infrastructure, and institutional factors. The county-level effects are modeled using a Besag-York-Mollié (BYM) structure which includes both exchangeable (iid) county random effects as well as conditional autoregressive structured (iCAR) residuals between counties. This formulation accounts for both random variation in yields across counties as well as spatial autocorrelation in yields across neighboring counties. *Percent_Irrigated* and *Percent_Crop* are linear controls that indicate the percent of irrigated land in a county and the percent of the county farmed with the crop of interest in each year, respectively. These controls account for known county characteristics that are expected to significantly impact yields. While most of the variance associated with these control variables is captured in the county-level spatial effects these variables are included as explicit controls in order to reduce chances of omitted variable bias (Blanc & Schlenker, 2017; Schlenker, Hanemann, & Fisher, 2007). Climate (*TP, GDD, SDD)* and diversity predictors (*D,* which includes SDI, SIDI, and RICH) are modeled using a first-order random-walk functional form. The random-walk structure allows the effect of these predictors to vary non-linearly (for example both low precipitation and very high precipitation tend to be associated with low productivity while moderate levels of precipitation tend to be associated with high productivity) while also considering that the effect of these predictors will be autocorrelated (e.g. similar values of TP will have a similar effect on yields).

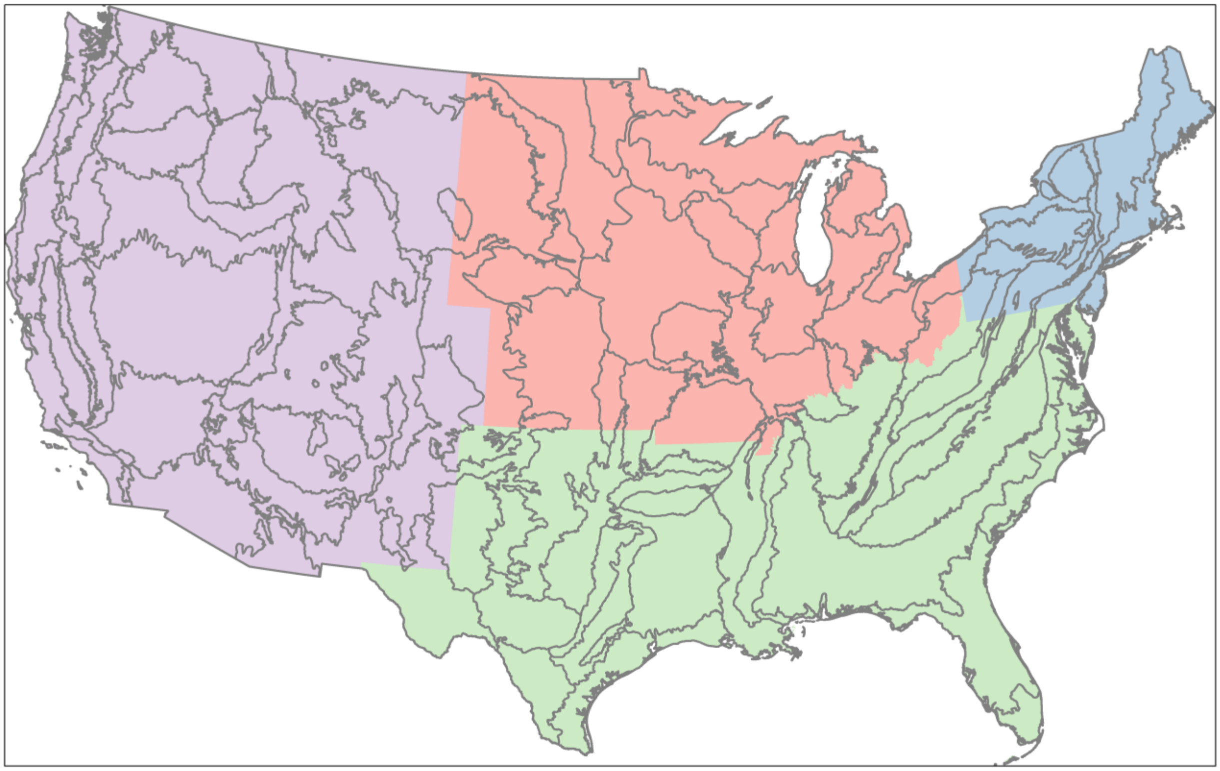

Figure 3: Gray lines indicate the Level III ecological regions (US EPA, 2011) used for the quadratic time-trends. Colored areas represent the four major regions used in the regional models described in the Results and Discussion.

Our Bayesian models utilize a highly uninformative (reduced precision) prior distribution for linear effects and employ penalized complexity (PC) priors for the diversity, climate, and spatial effects (Simpson et al., 2017). The PC priors employ a scaling factor to specify priors based on sensible limits of the data (Simpson et al., 2017). We employed default and recommended settings for PC priors as provided by Simpson et al. (2017), yielding moderately informative priors. Model fit was evaluated using the deviance information criterion (DIC), the conditional predictive ordinate (CPO), the predictive probability integral transform (PIT), posterior predictive p-values, mean squared error (MSE) and Bayesian R-squared (R^2) (Blangiardo & Cameletti, 2015; Gelman, Goodrich, Gabry, & Ali, 2017; Gelman, A., Hill, J., 2007). Cross-validation of final models was conducted by re-estimating models with ~86% of the observations and comparing model predictions against the remaining held-out observations using MSE, R^2, and the Nash-Sutcliffe Efficiency (NSE). In addition, model robustness checks were conducted to test sensitivity of results to the presence of control variables, data subsets, and prior specification (Schlenker, Hanemann, & Fisher, 2007). All models were estimated using the R-INLA package (Rue, Martino & Chopin, 2009) in R (R Core Team, 2014). Model scripts and additional information on model diagnostics and robustness checks are provided in the SI Appendix and on GitHub (https://github.com/eburchfield/Diversity_yield).

3.0 RESULTS

Our results estimate the nonlinear response of the yields of corn, soy, and winter wheat to changes in agricultural diversity as measured by the Shannon Diversity Index (SDI), Simpsons Diversity Index (SIDI) and Richness (RICH) (Figure 4). The response curves indicate that the yields of corn and winter wheat increase by between 5 and 20% respectively at high levels of agricultural diversity, which equates to approximately 22-33 bushels per acre for corn (~1,381 to 2,071 kg/ha) and 9-14 bushels per acre for winter wheat (~605 to 942 kg/ha). Soy is less responsive to agricultural diversity, with yield gains between 0 and 5% (up to 2.2 bushels per acre or ~148 kg/ha) at high levels of diversity. This aligns with published research showing that soy is less responsive to agricultural diversification (Smith et al., 2008) and changes in tillage and weather variability (Gaudin et al., 2015). Our results also indicate that the yields of corn and winter wheat are more responsive to SDI and RICH (Figure 4A and 4C) than SIDI (Figure 4B). These effects are detected after controlling for seasonal weather, county-level spatial effects, regional time trends, cultivated extent, irrigated extent, and spatial dependencies in the data. Table 2 shows high model fit across crops and diversity indices with posterior predictive and cross-validation R^2 values of more than 0.7 for all national models.

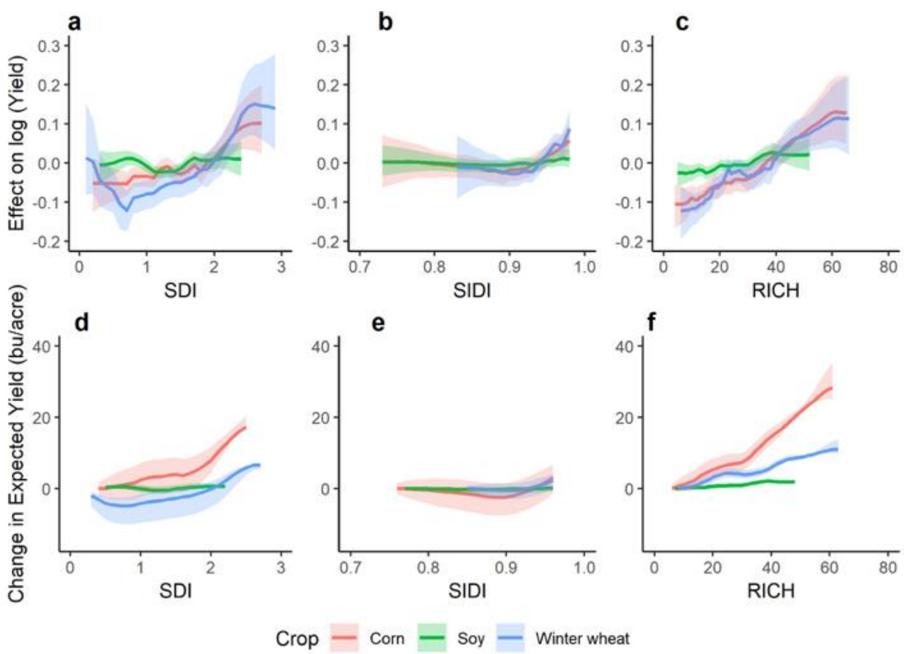

Figure 4: The impact of agricultural diversity as measured by the Shannon Diversity Index (SDI), the Simpson Diversity Index (SIDI), and richness (RICH) on yields for corn, soy, and winter wheat for counties in the coterminous U.S. Solid lines represent the median effect and the shaded bands represent the 95% credibility limits. Effects on log(yield) as seen in (a), (b), and (c) can be interpreted as a percent change in the actual yield associated with a specific value of each index. Plots (d), (e), and (f) shown the expected change in actual yield (bushels per acre).

Table 2: Model fit, posterior predictive checks, and cross-validation.

		Corn (n=11,085 county-years)			**Soy** (n=9,825 county-years)			**Winter Wheat** (n=8,003 county-years)		
		SDI	SIDI	RICH	SDI	SIDI	RICH	SDI	SIDI	RICH

Posterior Predictive Checks	MSE	0.0289	0.0289	0.0289	0.0174	0.0174	0.0174	0.0281	0.0281	0.0280
	R^2	0.7084	0.7082	0.7080	0.7521	0.7518	0.7522	0.7682	0.7687	0.7692
Cross-Validation	R^2	0.7397	0.7857	0.7112	0.7331	0.7736	0.7599	0.7362	0.7669	0.7940
	MSE	0.0423	0.0382	0.0413	0.0242	0.0258	0.0246	0.0391	0.0404	0.0404

Our models also produce crop-specific response curves to seasonal weather (Figure 5). Estimated yield-weather interactions resemble those in the published literature, indicating that more GDDs increase yields, while higher SDDs decrease yields (Schlenker & Roberts, 2009). The idealized TP-yield curve is an inverse parabola (Rosenzweig et al., 2014), reflecting damages to crop production under extremely low and high precipitation conditions. Corn and soy exhibit this response, while winter wheat yields increase only at high levels of precipitation. This may be attributable to the fact that unlike corn and soy, which are grown over the summer and harvested in early fall, winter wheat is planted in the fall and is harvested for grain the following spring. For all crops, very low seasonal precipitation is associated with higher yields. This may be due to the relatively short time-frame of our panel (2010-2016) as well as the importance of irrigation as a buffer against low precipitation over this period.

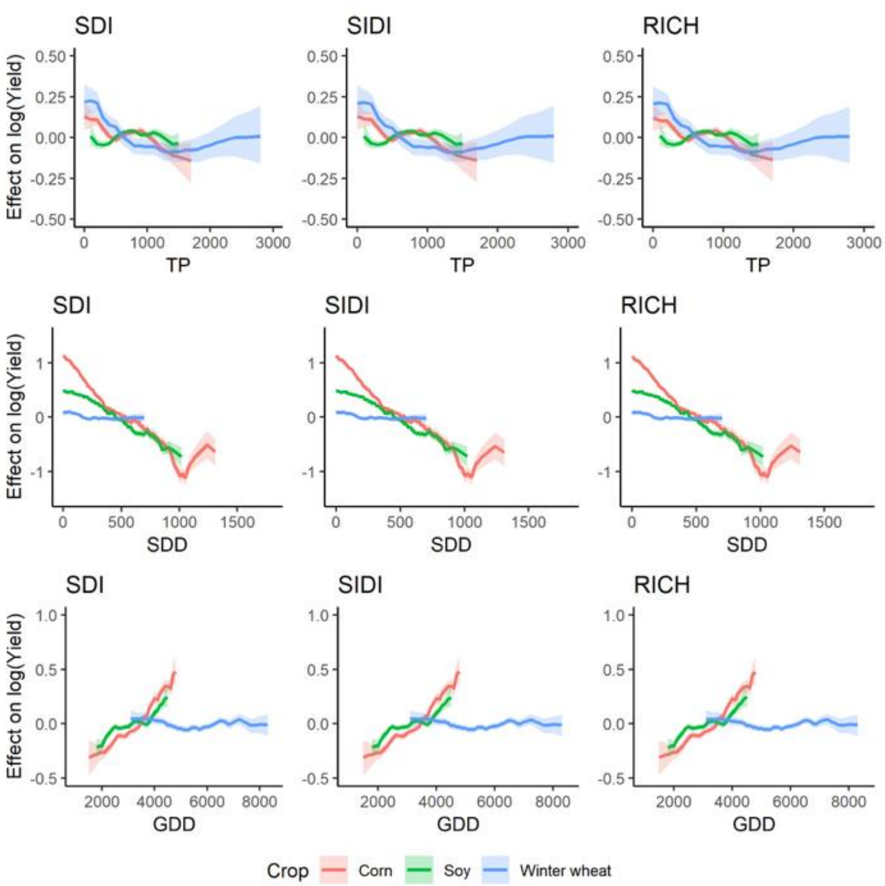

Figure 5: The response of yields to changes in total seasonal precipitation in millimeters (TP), growing degree days (GDDs), and stress degree days (SDDs) in degrees Celsius.

While the national models *control* for regional differences, they do not explicitly *model* the ways in which these differences influence diversity-production interactions. To assess how the relationship between agricultural diversity and crop production varies across space, we re-estimated models in four major regions of the U.S.: the South, Northeast, Midwest, and Western U.S. (Figure 3). The models suggest that in places where large-scale farming is less common for edaphic, topographic, cultural, or infrastructural reasons—such as the Southern and Western U.S.—agricultural diversity has a far greater impact on crop production (Figure 6). Midwestern and Northeastern agricultural systems are relatively insensitive to diversification, while Western systems show strong and sustained yield responses to all indicators of diversity. The Southern U.S. shows the most variability across crops, with positive yield responses for corn and soy, and slightly negative yield responses for winter wheat.

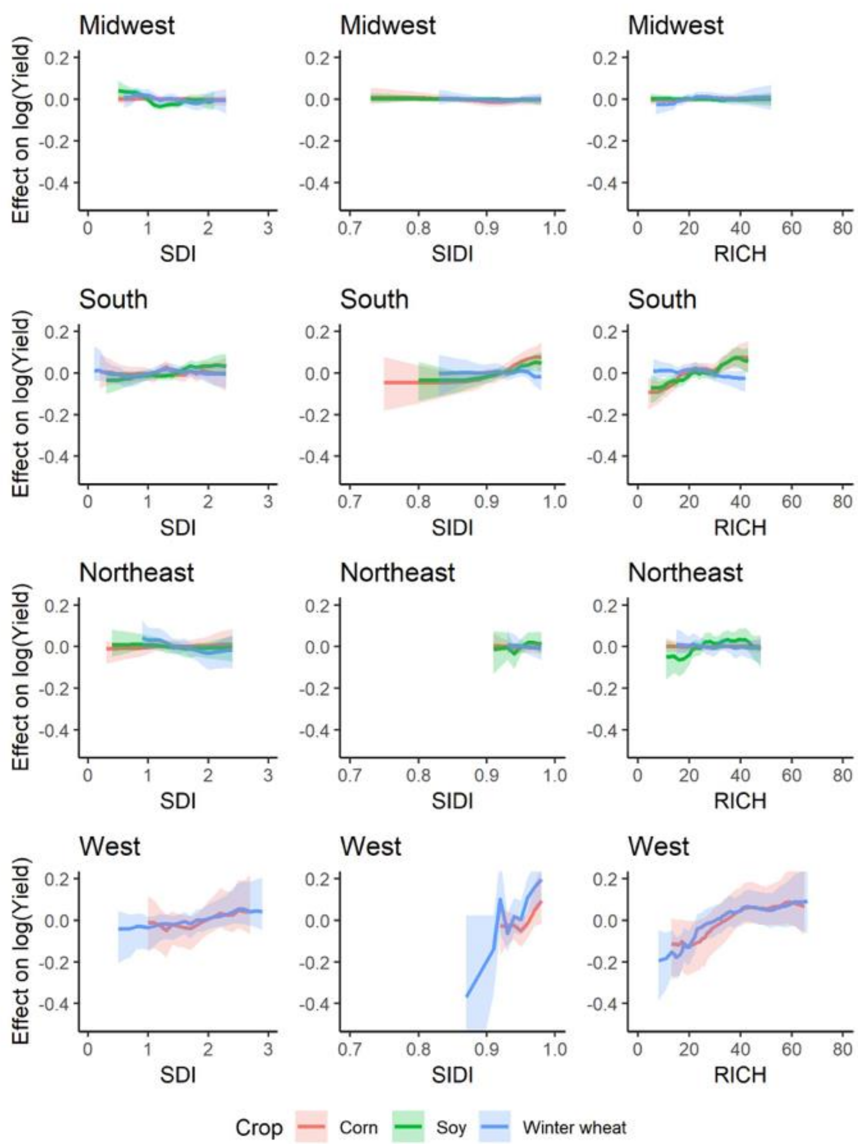

Figure 6: Regional differences in the effect of agricultural diversification on crop production.

4.0 DISCUSSION

Our results suggest agricultural diversification can directly benefit agricultural systems. Yields of corn and winter wheat increase by as much as 20% in highly diversified agricultural systems, and soy yields increase by nearly 5%. Our findings also indicate that (1) crop production is more responsive to the *number* of agricultural land use categories in a region than the relative cultivated *extent* of each category and that (2) increasing agricultural diversity in regions that are already diverse brings the highest yield gains. These results provide strong empirical support for *why* we should consider agricultural diversification. In what follows, we discuss how these models can also give us a better sense of where, when, and how to diversify.

4.1 Where to diversify? The importance of regional variability.

We find that agricultural diversification has a stronger impact on corn and winter wheat than soy nationally, but these effects vary across regions (Figure 6). For example, winter wheat shows markedly different responses to increased agricultural diversity in the Western and Southern U.S., while soy – relatively unresponsive to diversification in the national models – shows significant responses to diversification in the Southern and Northeastern U.S. The regional models highlight two important findings. First, differences in diversity-productivity curves across crops and indices as seen in the national models are less significant than differences in diversity-productivity curves across regions. This suggests that regional factors may play a larger role in moderating the diversity-productivity relationship than crop- and index-specific factors. Second, the regional models correspond with published literature indicating that the ways in which diversity interacts with crop production varies significantly across agricultural, climatic, ecological, and socio-cultural contexts (Balvanera et al., 2006; Loreau et al., 2001; Swift et al., 2004; Tilman et al., 2014; Zak et al., 2003). The spatial variability of our findings highlights the fundamental challenge of *scale* in agro-ecological research. Large scale models, such as those presented in this paper, provide empirical support for interventions that may sustainably increase agricultural productivity, but are limited in their ability to provide context-specific recommendations to support agricultural decision-making. Conversely, field-scale analyses can provide specific recommendations for farmers but are limited in their generalizability across regions.

Despite regional variability, in very few cases does diversification *decrease* yields. A shift from low to moderate levels of agricultural diversity decreases yields for winter wheat (national model); however, this is only the case for SDI, suggesting that how land uses are partitioned, as opposed to the number of land uses itself, is driving this effect. Increasing diversification is also associated with decreased winter wheat yields in the Northeastern and Southern regional models and with decreased soy yields in the Midwestern regional model, however these decreases are not significant.

4.2 When to diversify? The importance of contextual variability.

Our primary objective in modeling yield response to multiple indicators of diversity (SDI, SIDI, RICH) is to test model sensitivity to operationalizations of diversity; however, model differences also provide insights into how agricultural systems respond to different facets of diversity. Our results indicate that the yields of corn and winter wheat are more responsive to SDI and RICH (Figure 4A and 4C) than SIDI (Figure 4B). The SIDI is less sensitive than SDI and RICH to rare land use categories, meaning that a small increase in agricultural diversity in a system dominated by a single crop will increase both the SDI and RICH much more than the SIDI. Therefore, the relative responsiveness of corn and winter wheat yields to changes in SDI and RICH suggests that these crops are more sensitive to the *number* of distinct crops in a county rather their relative cultivated extent. This finding merits further exploration, as it indicates that cultivating small areas of a landscape with a new crop could increase agricultural productivity.

By estimating non-linearities in the diversity-productivity relationship, we can also identify the specific ranges of agricultural diversity that have the highest potential impact on crop production. The linear response of yields to RICH indicates that adding a new crop to an agricultural system operating at any level of diversity can increase yields; however, the shape of the SDI and SIDI curves in Figure 4 suggests that increasing agricultural diversity in systems that are already diverse brings the highest yield gains. For example, increasing SDI from 2 to 3 increases yields of corn and winter wheat by approximately 10 and 20% respectively. Similarly, increasing SIDI from 0.9 to 1.0 increases yields of corn and winter wheat by nearly 10%. Yield gains for corn and soy are much lower when systems move from low to moderate agricultural diversity. In the case of winter wheat, diversification in this range may actually decrease yields. We hypothesize that this is, in part, due to heavy reliance on external mechanized and chemical inputs in specialized monoculture systems that offset (at least in the short-term) the negative impacts of diversity loss.

Increasing agricultural diversity in regions that are already diverse has positive effects on yields of all crops across indicators of diversity and across regions. There is far more variability in crop response to diversification in systems with low agricultural diversity. These findings emerge both at the national and regional scales, with the Midwestern U.S.—a region dominated by monoculture systems—showing weaker yield responses to agricultural diversification than other regions of the U.S. This illustrates the importance not only of the regional variability discussed above, but of contextual variability, or the impact of current landscape composition on the effectiveness of diversification.

Figure 7 classifies systems in terms of their combined diversity and productivity. Diverse and productive systems are shown in dark green, while simplified and productive systems—largely concentrated in the Midwestern U.S.—are shown in dark purple. This figure highlights the importance of regional variability in diversity-productivity interactions but can also help to target regions where agricultural diversification may have the highest impact. Given our finding that agricultural diversification has the highest impact in systems that are already fairly diverse, diversification efforts targeted in regions of low to moderate agricultural productivity and moderate to high agricultural diversity (light greens and yellow regions) may have the highest impact.

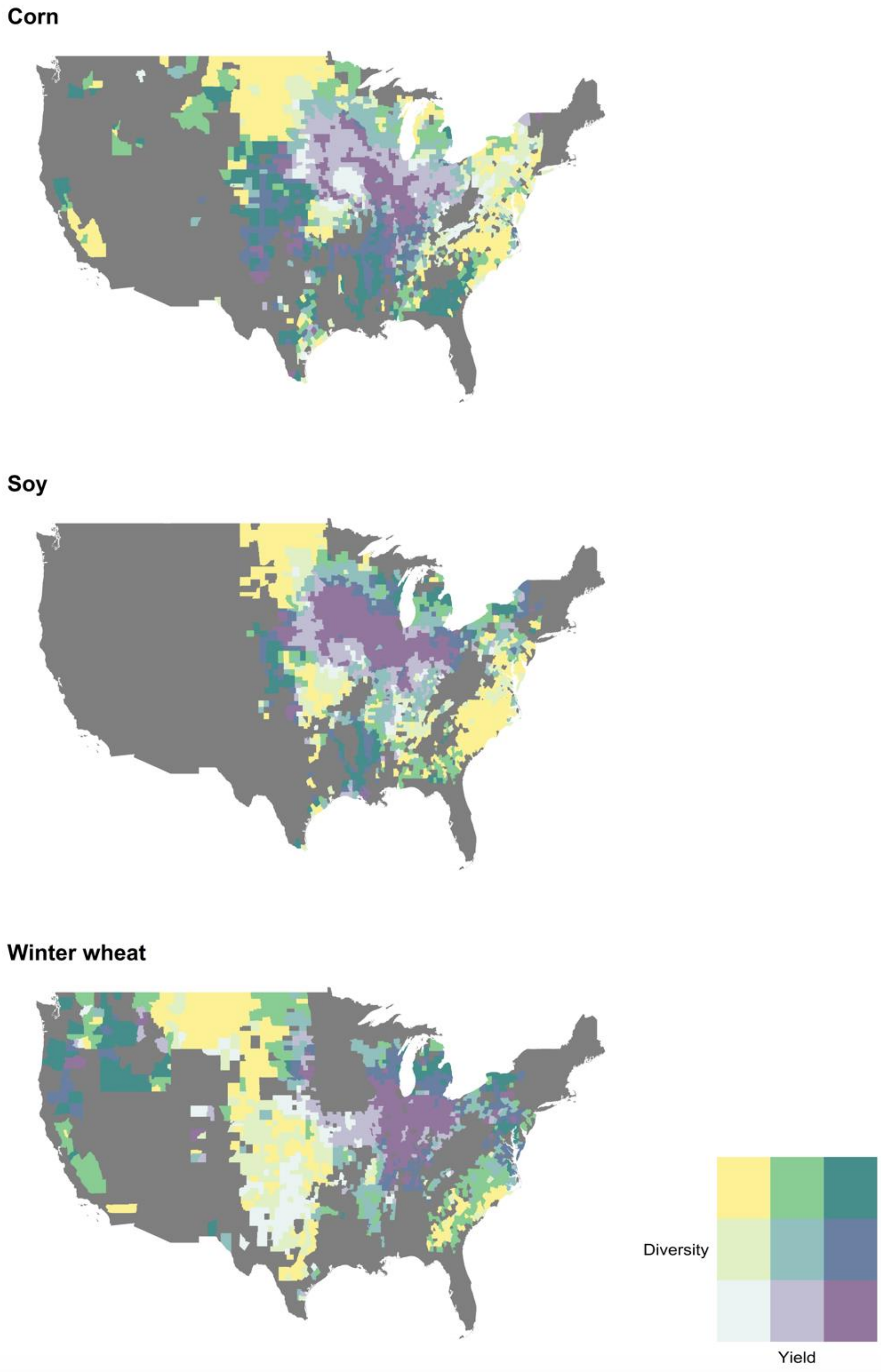

Figure 7: Bivariate choropleth constructed by binning county-level spatial effects and SDI into thirds. We use the county-level spatial effects from the model described in Section 2.2 run without diversity predictors as our indicator of yields. These effects capture the average yield in a county given the non-diversity predictors in our model (seasonal weather, irrigation, and acreage). Regions in dark green are both highly diverse and highly productive. Yellow regions are highly diverse, but low productivity, and purple regions are highly productive but low diversity.

Why might simple agricultural systems exhibit a more varied response to diversification than diverse agricultural systems? Simple agricultural systems, such as the monoculture systems that dominate much of the Midwestern U.S., tend to be highly specialized, intensively managed, and heavily reliant on external petro-chemical and mechanical inputs (Altieri, 1999; Foley et al., 2011; Kremen, Iles, & Bacon, 2012). These systems have some of the highest yields on the planet (USDA-FAS, 2017); however, these yields are not without environmental consequence (Rabalais et al., 2002; Kremen & Miles, 2012). We hypothesize that benefits from diversification in these systems are drowned out by the yield gains brought by intensive management. We note that, except in the case of winter wheat in a subset of models, crop production does not *decrease* with diversification. In fact, yield responses to RICH are near-linear in national models and consistently positive in the regional models across all crops. While we acknowledge the significant cost and barriers to diversification in monoculture systems (Blesh & Wolf, 2014; Roesch-McNally et al., 2018; Lin, 2011; Roesch-McNally, Arbuckle, & Tyndall, 2018), this result suggests that simple interventions, such as adding a small area cultivated with a new crop, could significantly increase crop production even in the most simplified systems.

4.3 How to diversify? A landscape "commons"

This investigation of the relationship between agricultural diversity and crop productivity has important implications for farmers and land managers across the U.S. Our results suggest that by increasing the compositional heterogeneity of crops within a landscape, farmers can significantly increase yields. Furthermore, our models suggest that it is the *number* of crops cultivated rather than their cultivated extent that can bring greater yield benefits. This suggests that relatively simple interventions such as adding a new crop cultivated on a small extent could increase agricultural system productivity. This also implies that a single farmer does not necessarily need to abandon monoculture to see yield gains; conversely, a diversified farmer may not see gains in productivity when cultivating in a simplified landscape. These dynamics emphasize the importance of conducting analyses at a *landscape* scale and of re-conceptualizing working landscapes, as well as the ecosystem services they generate, as common pool resources (Ostrom, 1990; Zhang et al., 2007). The benefits of agricultural diversification flow across property boundaries and associated costs may not be fairly spread across users. There is a growing need to understand land use diversification beyond individual farmer decisions and within the feasibility of coordinated landscape management and connectivity (DeClerck, Estrada-Carmona, Garbach, & Martinez-Salinas, 2015).

5.0 CONCLUSION

Human-induced reductions in diversity have had negative impacts on ecosystem function comparable to those from elevated carbon dioxide concentrations, nitrogen deposition, fire, and drought (Hooper et al., 2012; Tilman, Reich, & Isbell, 2012). Agriculture is a significant driver of this diversity loss and will likely remain as such if current practices persist (Bommarco, Kleijn, & Potts, 2013; Hendrickx et al., 2007; Landis, 2017; McDaniel, Tiemann, & Grandy, 2014; Tiemann, Grandy, Atkinson, Marin-Spiotta, & McDaniel, 2015; Tscharntke et al., 2012). In this paper, we assess whether and how increasing agricultural diversity affects agricultural health and productivity. Our models provide strong evidence at national and regional scales that agricultural diversification—an intervention with known ecosystem benefits—can increase crop production. This suggests that agricultural diversification could serve as a key land use strategy to boost agricultural production while preserving ecosystem function and integrity. These findings are relatively consistent across crops, indices of diversity, and regions of the U.S. However, these findings do not identify the specific causal mechanisms underlying the relationship between landscape diversity and crop production. A limitation of this study is the inability to account for local-scale factors and sub-annual variability such as application of fertilizer and pesticides for which data availability is limited and natural disaster events (see Figure S1). The regional variability in our models, highlights the continued importance of local- and meso-scale analyses to assess the complex assemblage of socio-ecological factors that mediate the diversity-productivity relationship across space and time. In addition, the time frame for which the USDA Cropland Data Layer land use information is available limits this study to a relatively short window of time, making these model results more sensitive to annual variation as shown in Figures S2-S4. Additional research is needed to identify the social and ecological moderators of the diversity-productivity relationship and key barriers to diversification such as capital and cost, risk perceptions and behavior, market dynamics, institutional constraints, and changing climate (Burchfield & Poterie, 2018; Di Falco & Perrings, 2005; Roesch-McNally, Arbuckle, & Tyndall, 2018). Our hope is that the empirical evidence provided in this paper will motivate future initiatives to identify these barriers and moderators.

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