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Path dependencies in US agriculture: Regional factors of diversification

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ABSTRACT

Concerns of declining agrobiodiversity and widening socioeconomic inequities in United States (US) agriculture highlight the critical need for systemic change. Despite surmounting evidence of the field and landscape scale benefits of diversifying agricultural systems, path dependencies of US agriculture present barriers to such diversification pathways. This study aims to elucidate path dependencies of agricultural landscapes that (dis) incentivize crop diversification at the regional scale through two main research questions: 1) what are the biophysical and socioecological factors most predictive of agricultural diversity across the US; and 2) how do these factors vary regionally? Using a novel panel dataset constructed from several open-source databases, we use random forest (RF) permutation variable importance measures to identify and compare the factors most predictive of county-level crop diversity across nine US regions. Our results show that climate, land use norms, and farm inputs are consistently the most important categories for predicting agricultural diversity across regions; however, variability exists in the relative regional importance of variables within these categories. Thus, factors most strongly predictive of agricultural diversity across US landscapes operate distinctly at a regional level, emphasizing the need to consider multiple scales of influence. These distinct regional relationships contribute to path dependencies that present resistance to enhancing agricultural diversity. By more appropriately addressing the regional factors of US agricultural landscapes the constrain agricultural diversification, with an eye towards future cropscapes, we can shift current path dependencies toward a more resilient and adaptive US agricultural future.

1. Introduction

In the United States (US), the Green Revolution is failing to safely and sustainably meet the food production demands of a growing global population (Altieri and Nicholls, 2009; Gleissman, 2015). Although modern agriculture is becoming increasingly productive (ERS, 2019; Key, 2019; Pellegrini and Fernández, 2018; Ramankutty et al., 2018; Reganold et al., 2011), this productivity has come at the cost of ecological health and the wellbeing of farmers, farmworkers, and rural communities writ large (Aizen et al., 2019; Anderson et al., 2019; Benton, 2012; Burchfield et al., 2022; Petersen-Rockney et al., 2021; Prokopy et al., 2020; Spangler et al., 2020; Thaler et al., 2021). Corporate power and consolidation are rising in the agri-food sector, extending corporate influence and control over global agricultural markets and political lobbying (Clapp, 2018; Clapp and Purugganan, 2020). These forces are reducing farmer autonomy (Burchfield et al., 2022; Hendrickson et al., 2020) and reinforcing agricultural policies built upon socioeconomic inequity and injustice (Fagundes et al., 2019; Graddy-Lovelace, 2017; Hauter, 2012).

At the same time, agricultural production has become increasingly specialized for a decreasing number of crop species (Aguilar et al., 2015; Aizen et al., 2019; Auch et al., 2018; Baines, 2015), and large-scale farm consolidation is driving out smaller-scale operations (MacDonald and Hoppe, 2017; Paul et al., 2004). This consolidation has led to the agglomeration and intensification of commodity production, resulting in simplified agricultural landscapes and concomitant biodiversity loss (Grab et al., 2018; Nassauer, 2010; Tscharntke et al., 2005). Moreover, these simplified landscapes are heavily reliant on external chemical and financial inputs and less resilient to uncertainty and change (Kremen and Merenlender, 2018; Landis, 2017; Meehan et al., 2011; Spangler et al., 2020).

Given these urgent concerns, there is a critical need for systemic

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change in US agriculture. One crucial area for change is a shift away from simplified commodity agriculture by increasing the agrobiodiversity of agricultural landscapes. Agrobiodiversity refers broadly to the diversity of food and agricultural systems (Zimmerer et al., 2019). As Kremen et al., (2012, p. 44) states, "a farming system is diversified when it intentionally includes functional biodiversity at multiple spatial and/or temporal scales through practices developed via traditional and/or agroecological scientific knowledge." Increasing agrobiodiversity promotes greater multifunctionality – or multiple beneficial functions beyond food and fiber production – throughout the US agri-food system to support mechanisms that "(re-)link agriculture to society at large through a far wider range of interrelations than just large commodity markets" (van der Ploeg et al., 2009, p. S130).

One short term mechanism for increasing agrobiodiversity is crop diversification. Crop diversification includes temporal and spatial diversification practices that increase the number and type of crops grown in an area at any point in time and over several years. Prior research at the field scale strongly supports the benefits of greater crop diversity, namely improved crop yields (Pywell et al., 2015; Schulte et al., 2017; Smith et al., 2008; Virginia et al., 2018), decreased yield volatility over time (Gaudin et al., 2015; Li et al., 2019), improved pest management (Bommarco et al., 2013; Chaplin-Kramer et al., 2011), improved soil health (Albizua et al., 2015; Berendsen et al., 2012; Ghimire et al., 2018; McDaniel et al., 2014; Postma et al., 2008), and increased pollinator diversity (Guzman et al., 2019; Schulte et al., 2017).

Furthermore, crop diversification at the field scale is embedded within multiscale landscape dynamics that serve a critical role in managing for and maintaining greater crop diversity at other scales (Birkhofer et al., 2018; iiPES-FOOD, 2016; Renting et al., 2009). An individual farm's ecosystem is both influenced by and influences the regional pool of crop and non-crop species and associated habitats. These interactions are referred to as the "landscape effect" (Benton, 2012, p. 9). In turn, greater crop diversity at the landscape scale can boost overall yields (Burchfield et al., 2019), improve yield stability to weather and climate volatility (Abson et al., 2013; Manns and Martin, 2018), support pest and disease control (Chaplin-Kramer et al., 2011; Gardiner et al., 2009; Ratnadass et al., 2012), and promote overall pollinator diversity (Hass et al., 2018; Tscharntke et al., 2005).

Despite the mounting evidence of the benefits of crop diversity, path dependencies in US agriculture present significant barriers to diversification. Path dependency can be defined as "resistance to changing the way things have always been done, even if business as usual seems to be increasingly maladaptive" (Barnett et al., 2015, p. 2). Increasing commodification of agricultural land use reinforces a high-yielding, productivist agricultural paradigm perpetuated by infrastructure, machinery, and institutional norms (Magrini et al., 2018, 2019; G. E. Roesch-McNally et al., 2018a). This self-reinforcing cycle may create resistance to change by "locking" farmers into certain technological and political regimes (e.g., pest management strategies, crop breeding, reliance on crop insurance, etc.) that are increasingly maladaptive to the implications of a changing climate (Annan and Schlenker, 2015; Chhetri et al., 2010) and other environmental shocks and stressors (Barnett et al., 2015). Crop diversification (and increasing agrobiodiversity more broadly) are important pathways toward more sustainable and resilient landscapes that work against these path dependencies.

Therefore, it is urgent to assess factors that help drive (or inhibit) crop diversity, particularly beyond the field scale, to understand how current path dependencies shape US agricultural landscapes. Biophysical realities of agricultural landscapes – climatic variability, water availability, and soil characteristics – shape and are shaped by processes of diversification or simplification, creating a baseline of environmental suitability for certain crops to grow and thrive (Burchfield and Nelson, 2021; Burchfield and Schumacher, 2020; Goslee, 2020). Yet, on-farm factors such as fertilizer use, labor, and irrigation play a crucial role in the success and stability of farm outputs (Burchfield and Schumacher, 2020), and government subsidies and assistance strongly influence farmer decision-making and priorities (Bowman and Zilberman, 2013; Graddy-Lovelace and Diamond, 2017; Zulauf, 2019). Thus, there is a pressing need to understand how biophysical realities, farmer decision-making, and government policy interact and influence the path dependencies that drive landscape simplification or diversification.

This study aims to elucidate path dependencies in US agricultural landscapes that (dis)incentivize crop diversification. In so doing, we address two main research questions: 1) what are the biophysical and socioecological factors most predictive of agricultural diversity across the US; and 2) how do these factors vary regionally? By focusing on the regional scale, we fill a research gap calling for a deeper understanding of human-environmental interactions at multiple scales across agricultural landscapes (Coomes et al., 2019; Duarte et al., 2018; Swift et al., 2004). In assessing how these factors are associated with agriculturally diverse or non-diverse landscapes, we aim to provide structural context for how and why farmers and farmworkers make decisions toward or away from diversification within these regions and landscapes.

2. Methods

We use random forest (RF) permutation variable importance measures to determine which biophysical and socioecological factors are most predictive of county-level crop diversity measures at the regional scale. These importance measures naturally account for interactive and/or non-linear effects among the predictor variables not possible in a standard correlation analysis. What differentiates our analysis from previous studies using RF is the focus on the predictive power of each explanatory variable, rather than simply focusing on accurate predictions.

2.1. *Predictor variables*

We utilized a novel panel dataset constructed from several open-source databases containing information about US agricultural land use, climate and soil characteristics, on-farm use of inputs and assistance, and farmer demographics. These data include observations for all counties in the coterminous US for the US Department of Agriculture (USDA) Census of Agriculture (COA) years 2012 and 2017, which are the most recent years available (USDA NASS, 2019a). The USDA COA is administered every five years to all farms and ranches selling at least $1000 of their products. It also includes irrigated extent from the Moderate Resolution Imaging Spectroradiometer (MODIS) Irrigated Agriculture Dataset (MIrAD) provided by the US Geological Survey (USGS) (Brown et al., 2019).

Although soil and climate data are available at much higher spatiotemporal resolution, the county-year is the finest spatiotemporal resolution at which COA data is publicly available nationally. Therefore, we aggregated all soil and climate data to the county-year scale. From 1-kilometer monthly climate summaries provided by the DayMet group (Thornton et al., 2017), we constructed nineteen indicators of average seasonal climate over the period from 2000 to 2020 (Fick and Hijmans, 2017) and extracted average seasonal values of these indicators for across all pixels in a county. To increase model interpretability, we only considered eight climatic indicators that are most predictive of crop suitability to include in our model prior to variable selection. We also included soil characteristics extracted from the Regridded Harmonized World Soils Database (FAO, 2012; Wieder et al., 2014) by extracting the average for soil attributes across pixels in a county. Once aggregated, we merged data into a county-year panel dataset for all counties in the coterminous US (n = 3108) for the years 2012 and 2017.

While we recognize the concern for the ecological fallacy associated with aggregating multiscale spatial data, we also acknowledge that there is no optimal scale at which all relevant ecological processes can be adequately explained (Harris, 2006), especially in a study that encompasses the entire US. One of the only reliable ways to mitigate this issue is to critically combine aggregated data with individual-level data

(Wakefield, 2007; Wakefield and Lyons, 2010); this is not possible for the scale of our models and the type of data necessary to capture the breadth of factors related to agricultural production and diversity. Furthermore, we have only included variables that are justifiably related to and influential of US agriculture production, supported by recent literature and relevant experts, to limit the estimation of spurious relationships (Salkeld and Antolin, 2020). Although obfuscating intra-county variability, the county scale is the finest resolution to include all relevant data in our models, and this study is a valuable step forward to encourage further intra-county analysis. For additional information and detail on methodological procedures, all code can be found on GitHub (github.com/kspangler1/regional-diversity).

2.2. Variable selection

Since RF permutation variable importance measures are negatively impacted by an excess number of highly related explanatory variables (Biau and Scornet, 2016), we performed a manual variable selection to minimize variable overlap based on both data availability and collinearity as foundational rules of elimination. First, we row-wise deleted any variables that were more than eight percent missing for both 2012 and 2017 and removed any variables that were a direct linear combination of any other variables.

We observed several pairs of highly collinear variables among the candidate explanatory variables (see SI Fig. 1A-1C for correlation matrices). For soil variables, we consulted with a soil health expert to rank all soil variables in order of priority (between one and three, one being top priority) as they relate to agricultural production (Cowan, 2020). Based on this expertise, we removed: 1) eight qualitative variables due to their redundancy and lack of interpretability; and 2) five quantitative variables based on high collinearity (correlation > 0.8) with variables of greater importance to agriculture that are more stable over time. For instance, topsoil pH was removed because it is actively managed for by farmers from season to season and therefore varies in many places across time and space, but we retained subsoil pH due to its relative stability over time (Ebabu et al., 2020; Metwally et al., 2019). For correlated climate variables, we assessed pairwise correlations by the following set of rules: 1) drop any climate variable that measures a range in favor of the minimum and maximum values; 2) drop monthly climate measurements and retain quarterly measurements; 3) retain any climate variable that is an annual summary. Finally, for highly correlated COA variables (rho > 0.8), we retained the variable with the higher availability.

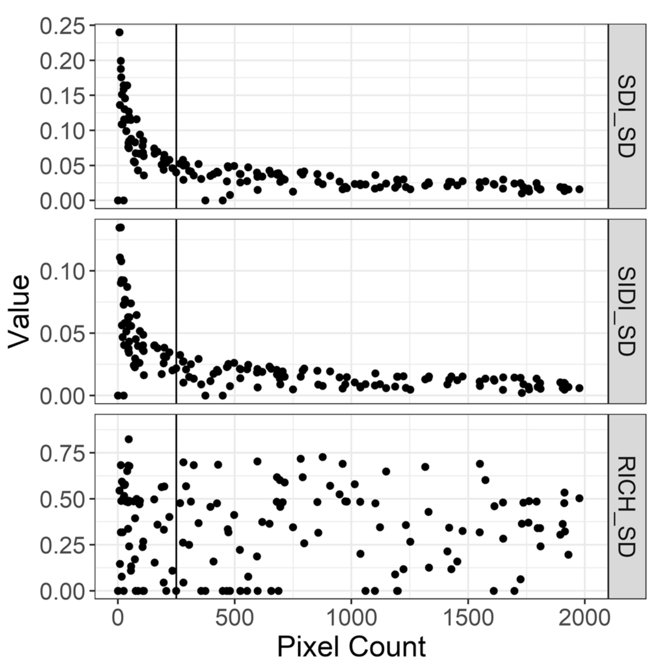

Fig. 1. Standard deviation of bootstrapped SDI, SIDI, and RICH plotted against number of agricultural land pixels (vertical line indicates 250-pixel cutoff).

2.3. Imputation

Following these variable selection processes, we would have removed 475 counties for 2012 (15.2% of all 3108 counties) and 422 different counties for 2017 (13.6%) due to missing COA data via row-wise deletion (for a total removal of 28.8% of counties across both years). To avoid this costly data removal, we performed imputation for missing data. First, we verified that the COA variables were not appreciably different between 2012 and 2017 by checking the distribution from 1997 to 2017 (see GitHub link to RF-imputation-COA.html). Given that all COA variables varied minimally from 2012 to 2017, we imputed missing data for counties in 2012 by infilling with its value in 2017, and vice versa. After systematically imputing these values, we deleted 134 counties in each year that had no data reported and, therefore, no data to impute in either year for retained COA variables.

2.4. Final predictor variables

Final predictor variables include measures of six main characteristic

Table 1
Predictor variable categories and units.

Variable	Units
Farm(er) Characteristics	
Primary producer's age	Avg. age
% acres operated by male farmers	% ag acres
Land tenure	% ag acres
On-farm experience	Avg. years
Farm size	Med. #
Farm inputs	
Fertilizer expense	$/ag acre
Manure acres	% ag acres
Chemical expense	$/ag acre
Irrigation	% ag acres
Labor	*n*/ag acre
Machinery	$/ag acre
Land use	
% cropland	% cty
% pastureland (excluding cropland)	% cty
Assistance & income	
Commodity sales	$/operation
Government programs	$/operation
Soil characteristics	
Topsoil gravel content	%vol.
Topsoil sand fraction	% wt.
Topsoil silt fraction	% wt.
Topsoil reference bulk density	Kg/dm3
Topsoil organic carbon	% weight
Subpsoil pH (H2O)	-log(H^+)
Topsoil CEC (clay)	Cmol/kg
Topsoil CEC (soil)	Cmol/kg
Topsoil calcium carbonate	% weight
Topsoil gypsum	% weight
Topsoil sodicity (ESP)	%
Topsoil salinity (Elco)	dS/m
Climate	
Mean annual temperature	°C
Mean diurnal range	°C
Temperature seasonality	sd* 100
Mean temperature of wettest quarter	°C
Mean temperature of driest quarter	°C
Mean temperature of warmest quarter	°C
Total (annual) precipitation	mm
Precipitation seasonality	coefficient
Precipitation of warmest quarter	mm

types: 1) farm(er) characteristics, 2) farm inputs, 3) land use, 4) assistance and income, 5) soil characteristics, and 6) climate (see Table 1 for variable descriptions). Variables were standardized (where applicable) using "total operated acres," which includes agricultural land used for crops, pasture, or grazing, as well as woodlands, farm roads, and farm buildings (USDA NASS, 2019b) (See SI Table 1 for full description of variables and their standardization). Further, given that our research questions aim to determine the influence of external factors on crop diversity at a moment in time, we did not include any lagged effects of prior crop diversity.

While this dataset contains a wide range of variables that are openly and reliably accessible, they are far from a comprehensive list of variables that are key to US agricultural path dependencies. They omit key demographic factors (e.g., race and ethnicity of both farmers and farmworkers), financial factors (e.g., corporate revenue and influence), and other important ecological factors (e.g., topography). These omissions limit our ability to build models that *explicitly* include sociopolitical processes that have been central to defining US agricultural landscapes and their current trajectories, such as Indigenous land dispossession and knowledge appropriation (Caradonna and Apffel-Marglin, 2018; Dunbar-Ortiz, 2014), racial discrimination (Ayazi and Elsheikh, 2015; Minkoff-Zern and Sloat, 2017), dismissal of queer rural identities (Dentzman et al., 2020), and corporate power over seeds, land, and trade markets (Baines, 2015; Clapp and Purugganan, 2020). However, such data have not been systematically or reliably collected for national or sub-national representativeness.

Nonetheless, these predictors do gauge several important factors that both drive current sociopolitical contexts and represent past sociopolitical forces to gauge what presents resistance to more diversified agricultural systems. These include: 1) reliance on external chemical and mechanical inputs (farm inputs); 2) binary gender-based differences in farm management (% acres operated by female/male farmers) in light of historical inequities in US agricultural land access for women (Carter, 2017); 3) the importance of land ownership (land tenure) and related experience (on-farm experience) in the context of the systematic exclusion of marginalized farmers and farmworkers in achieving such tenure and experience (Calo and De Master, 2016); 4) migrant and non-migrant farmworkers (number of laborers), particularly considering their inequitable legal representation and treatment (Soper, 2020), and 5) the significance of commodity production (commodity sales) and government assistance (government programs) as representations of the commodification and expansion of US production. We also include a suite of soil and climate variables to establish an understanding of biophysical suitability for crop diversity across regions.

2.5. Response variables

Response variables measure agricultural land use diversity through three metrics, computed using only agricultural land pixels from the USDA NASS Cropland Data Layer (CDL) (USDA NASS, 2020) and aggregated for every county in the coterminous US: Shannon's diversity index (SDI), Simpson's diversity index (SIDI), and Richness (RICH). SDI is one of the most common measures of landscape diversity, measured as the proportional abundance of each land use category in a county (Aguilar et al., 2015; Burchfield et al., 2019; Goslee, 2020; Gustafson, 1998). SIDI measures the probability that two random pixels (in the case of CDL data, 30-meter pixels) comprise different land uses and is less affected by rare land use categories than the SDI. Finally, RICH measures the number of agricultural land use categories (see SI Table 2 for full descriptions). These metrics operationalize crop diversity as both configurational (i.e., how much space each land use comprises) and compositional (i.e., what each land use is), accounting for spatial but not temporal variation within a given year.

Table 2
Summary statistics by FRR in 2017.

FRR	# of counties	Mean SDI value	Standard deviation of SDI
Heartland	540	0.91	0.16
Northern Crescent	388	1.11	0.35
Northern Great Plains	175	1.19	0.12
Prairie Gateway	373	0.97	0.29
Eastern Uplands	394	0.81	0.45
Southern Seaboard	461	0.94	0.36
Fruitful Rim	251	1.08	0.42
Basin and Range	169	0.87	0.38
Mississippi Portal	152	0.86	0.22

2.6. Reclassification of CDL data

While the overall cropland classification accuracy for the CDL dataset is notably high (89.4% in 2012 and 82.9% in 2017) (USDA NASS, 2021), crop- and region-specific classification accuracy rates are notably low (Reitsma et al., 2016). To address these error rates, we grouped functional crops together into broader categories – an approach recommended by Lark et al. (2017) – to improve data reliability. Broader categories were defined by the US National Vegetation Classification (USNVC) database (Faber-Langendoen et al., 2016) (SI Table 3). With this reclassification, we recalculated SDI, SIDI, and RICH for final analyses.

2.7. Bootstrap sensitivity analysis

Current approaches for estimating landscape diversity do not account for differences in the percentage of land devoted to agricultural land use. For example, prior to reclassification, San Francisco County, CA has only 39 pixels (30 m resolution) devoted to agricultural use, whereas Tioga County, PA has more than a half-million agricultural pixels. Both counties have an SDI score of 0.52, but the estimate for Tioga County is more reliable given its larger agricultural land area. Thus, we conducted a bootstrap sensitivity analysis (Efron, 1979) of the estimated diversity scores for each county. This analysis samples, with replacement, the parcels of agricultural land within each county. Each bootstrap sample is the same size as the original sample with some observations appearing more than once, and others not at all. In practice, roughly two-thirds of the original observations are represented in each bootstrap sample, and diversity scores are estimated for 500 bootstrap samples in each county. Fig. 1 plots the standard deviation of the bootstrapped diversity scores against the number of pixels devoted to agricultural land.

As expected, the sensitivity of SDI and SIDI are highly related to the number of agricultural pixels in each county. The standard deviation of the bootstrap diversity metrics levels out at roughly 250 pixels, so we removed any county with less than 250 pixels of agricultural land from our analyses. In total, a 250-pixel cutoff removed 39 counties for 2012 and 10 counties for 2017 after variable selection, imputation, and row-wise deletion. Of the 3108 total initial US counties, our final dataset included 2874 counties for 2012 and 2903 for 2017.

2.8. Analysis

Prior to analysis, we examined the distribution each response variable. SIDI was heavily skewed to the left, while SDI and RICH were normally distributed. We did not transform SDI and RICH, but since RF regression is not robust to the distribution of response variables, we transformed SIDI using a square transformation that substantially reduced the left skew.

We then divided counties into Farm Resource Regions (FRR) as defined by the USDA Economic Research Service (ERS) (Fig. 2). These

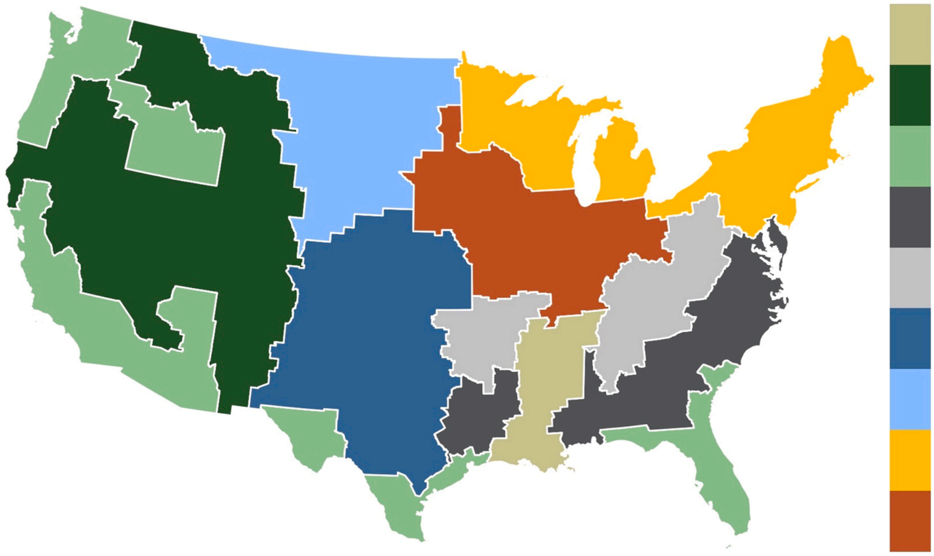

Fig. 2. Farm Resource Region (FRR) Designations.
Reprinted from Spangler et al. (2020).

regions reflect geographic specialization of agricultural production at the county-scale as determined by a cluster analysis of four other agricultural land use classifications: 1) USDA Crop Reporting Districts, 2) Land Resource Regions, 3) County Clusters of US farm characteristics, and 4) outdated USDA Farm Production Regions (ERS, 2000).

Using the randomForest package (Liaw and Wiener, 2002) in R (R Core Team, 2020), we built an RF regression model for all three response variables in 2012 and 2017 using all counties for each FRR (i.e., 3 models for each of the 9 FRRs in 2 different years, totaling 54 RF models). RF regression is a particularly adept method at handling complex, non-linear interactions among predictors with large datasets, and it does not require any distributional assumptions about the data. It has been used to accurately predict regional and global crop yields (Jeong et al., 2016), as well as regional crop diversity (Goslee, 2020). Due to prior research indicating the importance of increasing the number of trees to achieve stable variable importance (Grömping, 2009; Probst etal, 2019) we used 2000 trees per forest – four times the default value – to achieve stability without compromising accuracy. Variable importance measures were also shown to be insensitive to a doubling of the default value of mtry – the number of variables considered for splitting at each node of the tree. Given this insensitivity, all regional random forest models use default hyper-parameters with a fourfold increase in the number of trees fit in each model.

From each model, we assessed out-of-bag (OOB) percent variance explained from all variables, as opposed to cross-validated error using test and predictor subsets, because we were more interested in variable importance than predictive accuracy. Though there are many variations of the variable importance approach (Wei et al., 2015), we used permutation-based random forest variable importance (Breiman, 2001) given its widespread acceptance and use to compare the relative importance of the explanatory variables in each agricultural region. These relative measures are calculated by dividing the importance measures of each region by the maximum importance measure in each region.

Further, we recognize the presence and influence of spatial autocorrelation in these models. By visualizing the county-level residuals

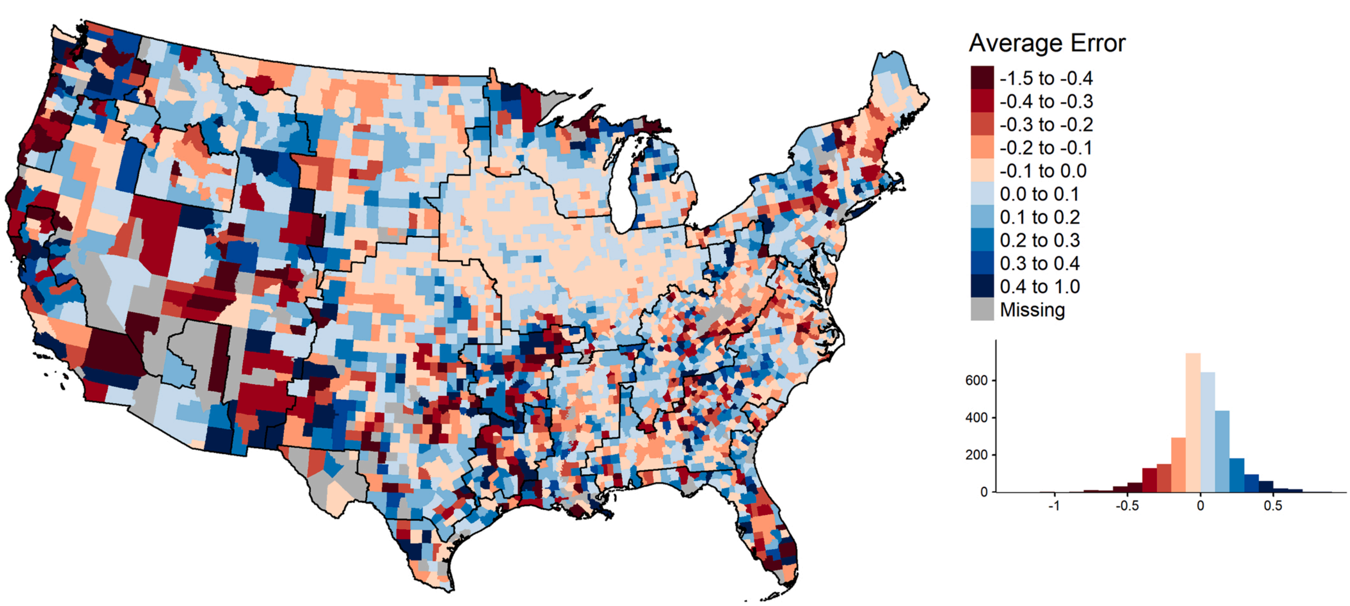

Fig. 3. RF regression model residuals for SDI in 2017; FRRs are outlined in black.

from our model predictions for SDI in 2017 (Fig. 3; see SI Fig. 2 for SDI in 2012), we show the distinct trends of positive (e.g., the Heartland) and negative (e.g., the Fruitful Rim) spatial autocorrelation within and across regions. However, we do not explicitly account for these trends in our models for two reasons. First, in regression scenarios, spatial autocorrelation can artificially inflate the statistical significance of beta coefficients, but we do not consider p-values to determine variable importance in this study. Second, while spatial autocorrelation can reduce predictive power, the focus of this paper is to quantify the predictive power of *external* factors (e.g., soil, climate, demographics, etc.) not to predict agricultural diversity most accurately. Thus, fitting a spatial model to these residuals would not change the story we tell regarding the importance of such external factors.

Finally, we assessed partial dependence of several of the most consistently important variables across regions from different predictor categories. Partial dependence plots are one way to visualize the marginal influence of a variable with a precedence for use in ecology (Cutler et al., 2007). These plots visualize the effect of a single variable on the prediction of diversity after accounting for the average effects of all other variables (Friedman et al., 2001), but are limited in visualzing variable interactions. We focused on six variables that were, consistently the most strongly predictive of diversity across regions: 1) temperature seasonality, 2) precipitation seasonality, 3) percent cropland, 4) percent pastureland, 5) chemical input, and 6) fertilizer input.

3. Results

We focus our results on SDI – the most widely used metric of agricultural diversity – and on 2017 – the most recently available year for Census of Agriculture data. Results from our other two response variables, and from 2012, are included in Supplemental Information (SI); the results of these analyses are consistent with our findings for SDI in 2017. First, we present summary statistics delineated by Farm Resource Region (FRR). We then provide the results of the regional RF regression models, specifically 1) how variables most strongly associated with agricultural diversity (variable importance) vary across regions, and 2) how these variables differentially influence regional diversity (functional relationships of key variables). We conclude by discussing the implications of these models and by contextualizing them within broader conversations about agricultural diversification.

3.1. Descriptive statistics

Mean regional SDI for 2017 ranges in between 0.81 and 1.19 for 2017, with the lowest mean value in the Eastern Uplands (0.81) and the highest in the Northern Great Plains (1.19) (Table 2; see SI Table 4 for 2012 data). Unsurprisingly, the Heartland region, which has the greatest number of counties (540), has a low average SDI (0.91) as well as a low standard deviation (0.16), indicating that this region is both agriculturally less diverse than most other regions and counties there within are more homogenous. The Mississippi Portal is the smallest region (152 counties) and has both a low SDI and standard deviation value. Like the

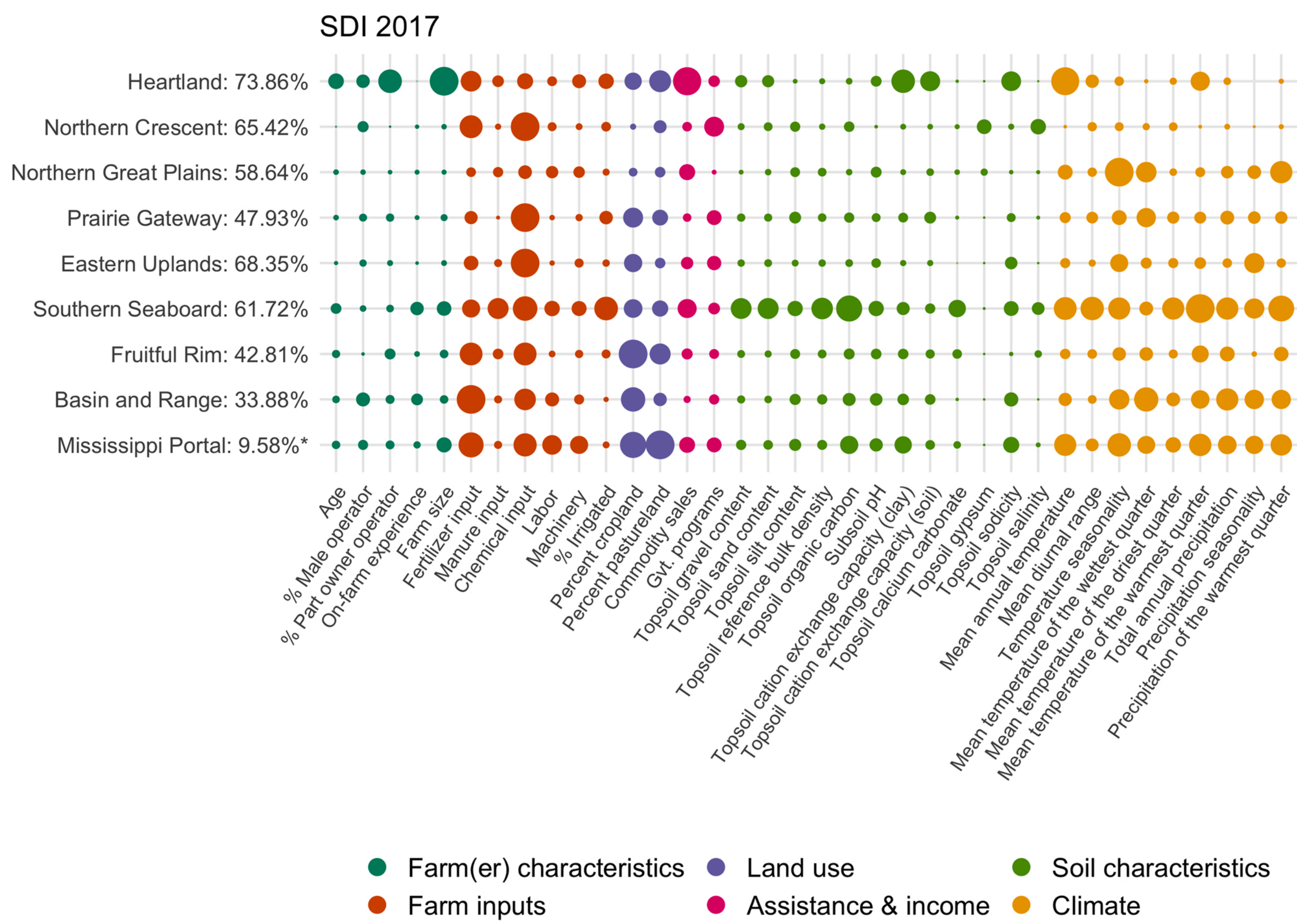

Fig. 4. Variable importance by FRR for SDI in 2017. The size of the bubble indicates variable importance: the most important variables are the largest bubbles, and the size of the bubbles in each region are standardized by the maximum importance measure in each region *The model for the Mississippi Portal only explains 9.58% of variance. We still included these results for consistency across models, but these results are not reliable.

Heartland, it is comparatively less diverse and more homogenous than other regions, particularly due to its small geographic area and a regional commodity focus on cotton, rice, and soybeans. The Fruitful Rim and Northern Crescent have comparatively high mean SDI values (1.08 and 1.11, respectively) and high standard deviations across counties (0.42 and 0.35, respectively). These divergences illustrate how landscapes within diverse regions have a wider range of heterogeneous farming systems across counties (e.g., high-end vegetable, fruit, and nut production in California) than less diverse regions.

3.2. Variable importance across regions

The relative importance of variable categories is consistent across regions (Fig. 4), with climate characteristics, farm inputs, and land use being the strongest predictors of SDI. This is also true for SIDI and RICH in 2017 (see SI Fig. 3A and 3B) and for all three response variables in 2012 (SI Fig. 4A-4 C). In the context of these models, soil characteristics, assistance and income, and farm(er) characteristics are less important predictors of regional agricultural diversity.

Although the variable categories predictive of diversity are consistent across regions, clear differences exist across regions regarding the distribution of variable importance. For regions such as the Northern Great Plains, specific climate variables (e.g., temperature seasonality) are substantially more important than most other variables in predicting SDI. This is also true for regions like the Northern Crescent, where farm input variables (e.g., chemical inputs) explain the majority of SDI variance. However, for the Heartland and Southern Seaboard, predictive importance is distributed more evenly across predictors. For these regions with more evenly distributed variable importance, soil and farm (er) characteristics are similarly important to climate, inputs, and land use, placing less predictive power on any one variable category.

In addition, model performance varies regionally. The two regions with the lowest mean SDI – the Heartland and Eastern Uplands – exhibit the highest percentage of variance explained (roughly 74% and 68%, respectively). This points to the ways that less diverse landscapes are easier to model and predict, particularly at a broader regional level. Nonetheless, the Northern Great Plains and Northern Crescent exhibit high average SDI values and comparatively high model performance (roughly 59% and 65% variance explained respectively). Importantly, the Mississippi Portal, one of the least diverse regions, exhibited an unreliably low model performance of less than 10% variance explained. This highlights the importance of intra-regional dynamics that are difficult to consistently capture at larger spatial scales, and the data-hungry nature of RF modeling.

3.3. Functional relationships of key variables

The partial dependence plots of several variables that were consistently important (Figs. 5–7) show the diverse ways that farm inputs, climate, and land use influence crop diversity, emphasizing the presence of regionally specific drivers of agricultural production – some that can be managed for and some that cannot. First, we consider the overall importance of climate in predicting crop diversity and defining biophysical suitability for certain crops; Fig. 5A and 5B illustrate the functional relationships between temperature seasonality (A) and precipitation seasonality (B) with SDI. As temperature seasonality (TS) increases (or as temperatures become more variable) in the Eastern Uplands and Fruitful Rim, SDI sharply increases and then plateaus, indicating wide temperature ranges across counties in each region that influence the diversity of crops grown. Yet, all other regions exhibit a slightly negative or neutral trend between TS and SDI: as TS increases, SDI decreases or stays the same, indicating that places with more seasonal temperatures do not inherently support greater crop diversity. A similar trend is observable with precipitation seasonality (PS) (or the variability of precipitation by season). For the Eastern Uplands, as PS increases, so does diversity; this is particularly true for counties well above the regional mean PS value. This means that counties in this region with the highest PS are much more likely to support a greater diversity of crops than those with less PS. For the Northern Crescent and Southern Seaboard, there is a slightly positive effect on SDI as PS increases; this positive relationship occurs for the counties with an average PS value. For all other regions, there is no observable positive or negative effect from PS, emphasizing how precipitation (as one of many important climatic factors) creates baseline conditions for agricultural production and possibilities for diversification, as opposed to being a factor that can be directly managed to increase crop diversification.

In terms of factors that can be directly managed, percent cropland and pastureland are highly predictive of crop diversity. Yet, percent cropland exhibits different functional relationships across regions (Fig. 6A). For the Northern Crescent, Eastern Uplands, and Southern Seaboard regions, there are discernable positive relationships between percent cropland and SDI, where counties with more croplands show higher levels of agricultural diversity. These positive relationships occur for the counties with percent cropland close to the regional mean. In the

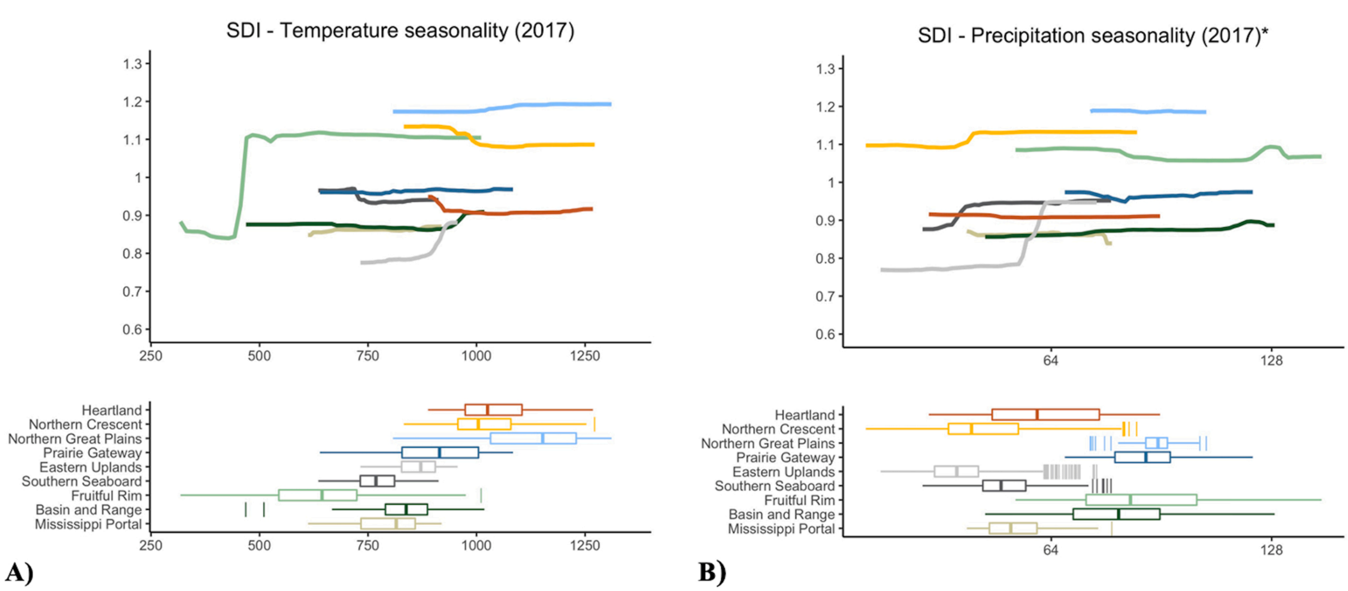

Fig. 5. Partial dependence plots of temperature seasonality (5A) and precipitation seasonality (5B) as a function of SDI in 2017.

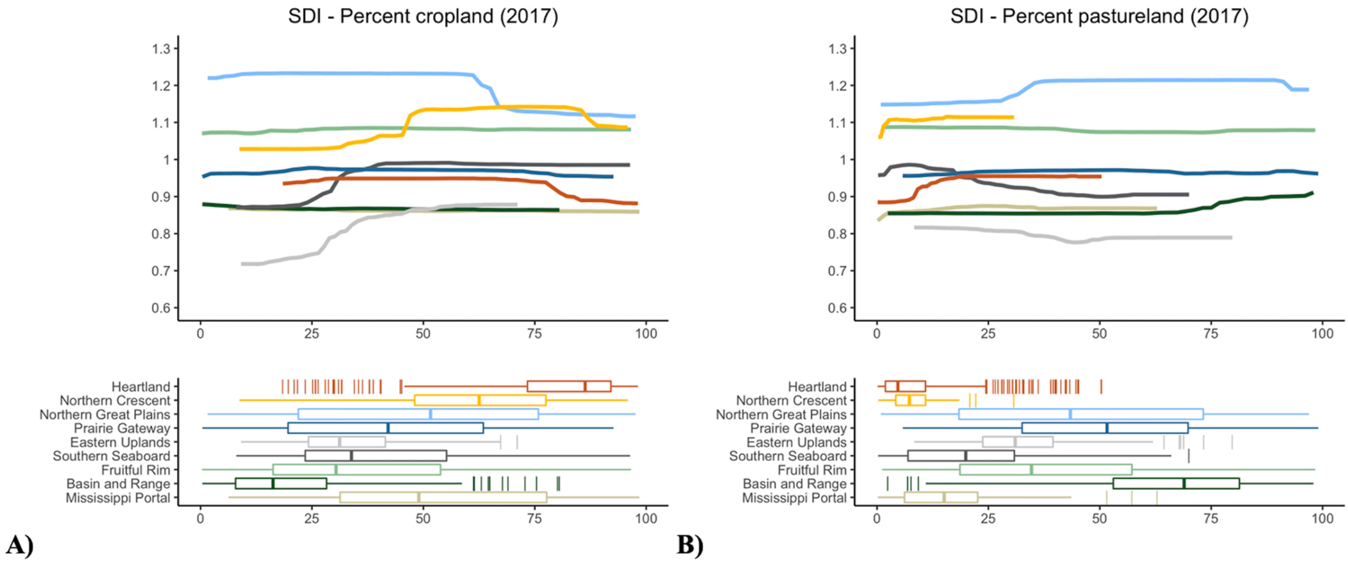

Fig. 6. Partial dependence plots of percent cropland (6A) and percent pastureland (6B) as a function of SDI in 2017.

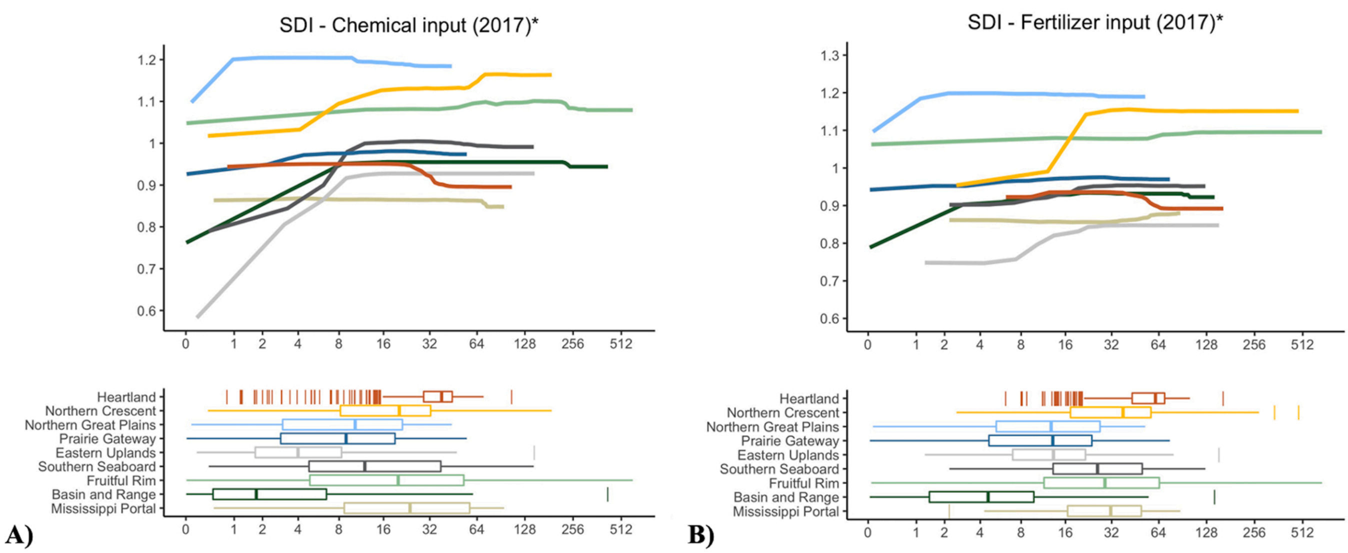

Fig. 7. Partial dependence plots of chemical input (7A) and fertilizer (7B) as a function of SDI in 2017 *Data are visualized on the log scale to better visualize the lower end of the highly skewed data. Notice that each tick mark on the x axis represents a doubling of the previous value, rather than a fixed increment between values.

Heartland and the Prairie Gateway, the opposite is true: for counties with percent cropland close to the regional mean, SDI begins to decrease. Moreover, counties in the Heartland have the highest average percent cropland of any region (~80%), reflecting its high concentration of simplified crop production. For the Fruitful Rim, Basin and Range, and Prairie Gateway, there is no effect between increasing percent cropland and SDI. This neutral relationship indicates that percent cropland is a highly predictive yet intrinsic factor in determining the diversity of crops grown in each region, and, thus, the directionality of its influence is indeterminable.

Percent pastureland (Fig. 6B) exhibits a neutral relationship in predicting SDI, with a few exceptions. For most regions, such as the Northern Crescent, Prairie Gateway, and Fruitful Rim, the effect of pastureland on predicting agricultural diversity is neither positive nor negative. Like cropland presence, the presence of pastureland within these counties is intrinsically important to the diversity of crops grown but does not increase or decrease such diversity. However, in regions such as the Heartland, Northern Great Plains, and Basin and Range, counties close to the regional mean of percent pastureland begin to increase in crop diversity until they eventually plateau again. This is particularly interesting for the Basin and Range, a region with the lowest average percent cropland and highest percent pastureland, indicating that pasture production is a strong driver of regional crop diversity. The only region where percent pastureland has a negative effect on SDI is the Southern Seaboard.

Other key factors that can be directly managed as strong predictors of crop diversity include fertilizer and chemical input. Crop diversity in all regions is highly responsive to expenditures on fertilizers and chemicals but quickly experiences diminishing returns. Moreover, the threshold of these diminishing returns is different for every region (Fig. 7A and 7B). Most notably, the Heartland is the region with both the highest average chemical and fertilizer expenses per acre; increasing chemical and fertilizer expenses both have an observably negative relationship with SDI. For counties at the regional average of input use, SDI begins to decrease and quickly plateaus; in other words, higher input use is associated with *decreasing* crop diversity.

Contrastingly, the Eastern Uplands, Basin and Range, and Northern Crescent regions exhibit the sharpest increase in crop diversity as chemical and fertilizer input use increases. These increases occur for counties close to the regional mean of input use and then plateaus, meaning that counties with the highest input use do not support greater crop diversity than those with average input use. Other regions, namely the Fruitful Rim and Northern Great Plains, consistently include counties with the highest SDI values and exhibit a neutral response to increasing input use, suggesting that their diversity is not dependent on their use of agricultural inputs.

4. Discussion

Our results show that factors most strongly predictive of crop diversity across US landscapes operate distinctly at a regional level. These distinct regional relationships contribute to path dependencies that present resistance to enhancing agrobiodiversity across US agriculture. First, major US regions exhibit significantly different levels of crop diversity, where the most diverse regions support a wider array of farming systems that deviate from the average, and the least diverse support more homogenous systems. Second, climate, land use norms, and farm inputs are consistently the most important categories for predicting agricultural diversity across regions; however, variability exists in the relative regional importance of variables within these categories. Model performance also varies, pointing to the existence of distinct intra-regional dynamics that we cannot explain at the regional level with the data we have included in these analyses. These intra-regional dynamics are evident in the various functional relationships between key climate, land use, and input variables for predicting diversity.

Regional differences in crop diversity, paired with the importance of climate, land use, and farm input variables in predicting such diversity, highlight the need to consider the regional scale and its influence on path dependencies in US agriculture. Our models illustrate clear and consistent trends that operate within and across nine US regions that may not be evident at the micro (field or farm) or macro (international) scales. For example, soil metrics did not prove to be as important a biophysical predictor as climate in our regional models, despite soil health and management being strong factors in understanding crop suitability (Zabel et al., 2014) and farmer decision-making (Roesch-McNally et al., 2018a) at the field scale. Furthermore, federal subsidy assistance and policies strongly dictate domestic and international markets, commodity supply chains, as well as farmer livelihoods and adaptation (Annan and Schlenker, 2015; Graddy-Lovelace, 2017; Graddy-Lovelace and Diamond, 2017), yet were not comparatively important in predicting regional crop diversity. Thus, considering multiple scales of interaction is crucial to a deeper understanding of what constrains and enables processes of diversification.

Climate characteristics play a pivotal role in defining the biophysical possibilities of regional crop and commodity production. Metrics of seasonal precipitation and temperature are consistently important factors in predicting agricultural diversity within and across regional landscapes. The strong importance of climate in predicting agricultural diversity underscores the importance of understanding how climate affects what farmers can reasonably do within a given landscape. This is particularly salient considering how climate change may shift the suitability of landscapes for major crops northward (Lant et al., 2016), increase the sensitivity of the agricultural economy (Liang et al., 2017), and contribute to greater yield variability globally (Ray et al., 2015). While climatic factors cannot be actively managed for to shift US agricultural path dependencies, it is increasingly important to consider how any volatility in current and future regional climates will likely have a strong effect on the potential for, and success of, diversifying agricultural landscapes.

The importance of land use patterns, namely the presence and concentration of cropland and pastureland, in predicting crop diversity across regions emphasizes how past land use reinforces current and future land uses. The importance of these factors captures the path dependencies that have determined where and why agricultural land is located and managed and highlights the growing resistance to changing these land uses. Our results show the regional specialization and intensification of commodity production, where agricultural landscapes are either dominated by crop production or rangelands and never equally covered by both (Spangler et al., 2020). The negative effect of increasing percent cropland on diversity in regions already largely dominated by cropland (e.g., Heartland) accentuates the self-reinforcing cycle of intensified commodity production; in this region, cropland expansion has driven and continues to drive the simplification of these landscapes (Hart, 1986, 2001; G. E. Roesch-McNally et al., 2018b). This history exacerbates the sociopolitical and ecological challenges of transitioning these landscapes toward alternative production systems (Lawler et al., 2014). Yet, for other regions less dominated by cropland (e.g., Eastern Uplands, Southern Seaboard, and Northern Crescent), the relationship between percent cropland and diversity is slightly positive. This finding presents broad evidence that allocating more land to crop production in *certain* regions may support greater crop diversity, provided such expansion is intentionally integrated with other socio-ecological benefits to the landscape (Kremen, 2015; Kremen and Merenlender, 2018). This is also true for increasing pastureland in regions such as the Basin and Range and Northern Great Plains, considering recent research that supports the potential for integrated crop-livestock systems as a viable pathway toward enhancing agrobiodiversity (Bonaudo et al., 2014; Franzluebbers et al., 2014; Olmstead and Brummer, 2008; Poffenbarger et al., 2017).

Finally, reliance on chemical and fertilizer use operates as a technological lock-in to current US agricultural path dependencies, unsustainably extending the viability of simplified systems. Mounting evidence illustrates the harmful environmental and social externalities of our increased reliance on external inputs to agriculture, including Gulf of Mexico hypoxia, nutrient runoff, decreased air quality (Prokopy et al., 2020), declines in pollinator abundance and diversity (Sponsler et al., 2019), and even decreased yields (Burchfield and Nelson, 2021). Our results show diminishing diversity returns from increased input expenditure, where crop diversity in many regions responded positively to increasing chemical and fertilizer expenditures initially, but quickly plateaued. This trend suggests that initial increases in crop diversity rely, in part, on increasing fertilizer and chemical inputs, which is consistent with the well-documented reliance on inputs throughout commercial annual cropping systems in the US (Culman et al., 2010; De Notaris et al., 2018; Gardner and Drinkwater, 2009). However, the diversity plateau in the fertilizer and chemical partial dependence plots provides compelling evidence that diversification beyond the regional status quo will not be driven by greater reliance on chemical and fertilizer use. Furthermore, for the Heartland, where intensified annual commodity production is most heavily concentrated (Hart, 1986; Hudson, 1994), the results suggest that excessive use of chemical and fertilizer use promote simplification and inhibit diversification of agricultural landscapes.

4.1. Future research

This study presents multiple future research directions. First, the definition of a region could be explored through various other regional boundaries to assess how this change in scale influences our results. Methodologically, regarding the bootstrap sensitivity analysis, we used a simple cutoff method to eliminate any counties below a threshold of reliability. One issue with a simple cutoff is that small changes to the boundary could potentially lead to large changes in the final outcomes. Therefore, future research could consider a weighting scheme that handles differences in the landscape metric sensitivities in a *continuous* way. Furthermore, it would be worthwhile to explore alternative methods and measures of variable importance to further corroborate the results discussed in this paper, as well as consider multi-level statistical methods to explore intra-regional mechanisms of crop diversity. Finally, we call for more research that explicitly considers the multiple scales of interaction that constrain and enable the efficacy and implementation of crop diversification (and policies that support it) from micro- to macroscales. There is strong potential for qualitative research to meaningfully build from these modeling efforts to facilitate the critical and intentional contextualization of how farmers and farmworkers across the US operate within, and respond to, heterogenous biophysical and sociopolitical contexts.

5. Conclusion

Developing pathways to alternative agricultural systems requires a fundamental reckoning with current path dependencies in US agriculture. We show that these path dependencies, and the associated lock-ins of current agricultural land use, operate distinctly within and across US regions. The consistent importance of biophysical and nonactionable factors, like climate, and actionable factors, such as land use and farm inputs, as highly predictive regional factors exemplify how these factors are deeply intertwined with the diversity (or lack thereof) of agricultural landscapes. These important factors, and their functional relationships with crop diversity, also highlight how *resistant* the systems within each region may be to alternative pathways and adaptation.

Imagining alternative, diversified agricultural systems – an increasingly urgent necessity in the face of a changing climate and widening sociopolitical inequity – requires a fundamental shift away from regional pathways that lock farmers and farmworkers into maladaptive systems. These pathways reinforce the current US productivist paradigm and the structural barriers to farmer adoption of alternative management strategies. As shown in this study, we can begin this shift by first integrating the importance of regional biophysical factors, namely climatic variability, into agricultural policies from local to federal levels, as well as prioritize climate adaptation for US agricultural systems. Second, the historical legacies of prior and current land use dynamics must be central to defining realistic alternative pathways of future crop diversification. For regions that have been and continue to be dominated by increasingly simplified cropland, these alternative pathways encounter greater resistance and will require distinct, innovative solutions as compared to regions that have been and continue to be more agriculturally diverse. Third, decreasing reliance on agrichemical inputs is a key priority for US agriculture writ large. While such inputs can extend the viability of simplified systems, there is an upper limit to this support; thus, we add to the growing call for US agriculture to promote more ecologically situated practices that *harness* ecosystem services rather than degrade them.

Agricultural diversity increases system resilience and has positive boundary effects for neighboring farm(er)s and ecological systems; by more appropriately addressing regional drivers of agricultural land use, with an eye towards future cropscapes, we can be sensitive to farm(er) concerns and needs while shifting current path dependencies toward more resilient and adaptive US agricultural landscapes.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.agee.2022.107957.

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