Landscape Complexity, Crop Insurance Losses, and Resilience to Extreme Weather Events

Yuyuan Che, North Carolina State University, yche3@ncsu.edu

Roderick M. Rejesus, North Carolina State University, rmrejesu@ncsu.edu

Serkan Aglasan, Mehmet Akif Ersoy University, saglasan@mehmetakif.edu.tr

Emily K. Burchfield, Emory University, emily.burchfield@emory.edu

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Yuyuan Che[†] Roderick M. Rejesus[‡] Serkan Aglasan[§]
Emily K. Burchfield[¶]

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Abstract

This study explores whether increasing landscape complexity reduces weather-related crop insurance losses. We utilize 2008-2018 county-level panel data with information on landscape complexity, crop insurance losses (i.e., due to drought, excess heat, and excess moisture), and a number of weather variables to achieve the study objective. Linear fixed effect models are used in the empirical analysis. Our results suggest that counties with greater landscape compositional complexity (e.g., higher Shannon diversity index) and greater configurational complexity (e.g., lower largest patch index) tend to have lower crop insurance losses due to excess heat or excess moisture. These results indicate that enhancing the complexity of landcover can enhance resilience to extreme weather events and facilitate adaptation to climate change.

Key words: climate change, ecosystem service, landscape diversity, weather resilience
JEL classification: Q15, Q18, Q54, Q57

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[†]Yuyuan Che is Postdoctoral Research Scholar, Department of Agricultural and Resource Economics, North Carolina State University

[‡]Roderick M. Rejesus is Professor & Extension Specialist, Department of Agricultural and Resource Economics, North Carolina State University

[§]Serkan Aglasan is Assistant Professor, Mehmet Akif Ersoy University

[¶]Emily K. Burchfield is Assistant Professor, Department of Environmental Sciences, Emory University

1 Introduction

Agricultural expansion and intensification have resulted in the simplification of Earth's landscapes over time (Aguilar et al., 2015; Landis, 2017; Burchfield, Nelson, and Spangler, 2019). In the United States (US), agriculture has covered more than 50% of the total land area, with a significant portion of agricultural land devoted to only three crops: corn, soybeans, and wheat (Bigelow and Borchers, 2012). This decline in landscape complexity has led to various adverse environmental consequences, including reduced water quantity and quality, land degradation, and loss of species diversity (McDaniel, Tiemann, and Grandy, 2014; Landis, 2017). Landscape complexity also influences essential ecosystem services that are crucial for agriculture (such as pollination, pest regulation, and carbon storage) (Li et al., 2009; Swinton et al., 2007; Duarte et al., 2018; Larsen and McComb, 2021).

Landscapes with higher levels of diversity and complexity have been shown to contribute to improved crop productivity (Burchfield, Nelson, and Spangler, 2019; Renard and Tilman, 2019; Nelson and Burchfield, 2021). Specifically, increasing landcover diversity has been associated with yield increases exceeding 10% for crops like corn and wheat. Moderately complex and highly diverse landscape configurations are associated with corn and wheat yield increases by more than 20% (Nelson and Burchfield, 2021). Therefore, enhancing landcover complexity presents a viable approach to improve crop productivity without further agricultural expansion or intensification (Nelson and Burchfield, 2021). Such an approach becomes particularly significant given the anticipated adverse impacts of climate change to agricultural production.

A substantial body of literature has provided evidence that climate change negatively impacts crop yields (Tack, Barkley, and Nalley, 2015; D'Agostino and Schlenker, 2016; Wang et al., 2021). In US agriculture, over 30% of historical crop yield losses can be attributed to extreme weather events, including droughts, extreme heat, and excess moisture (Skees, Barnett, and Collier, 2008). As climate change continues to amplify the intensity and frequency of these extreme events, understanding factors that can help mitigate the negative impact of these events on agricultural production becomes more and more important. However, little is known about how landscape complexity can affect production risks, particularly the risks from more severe and more frequent extreme weather events that can be attributed to climate change.

This study addresses the question of whether increasing landscape complexity can reduce weather-related production losses in US agriculture. Specifically, we examine whether counties with higher landscape complexity are more likely to have lower crop insurance losses due to three distinct extreme weather events: droughts, extreme heat, and excess moisture (e.g., floods). Hence, this study aims to assess whether enhancing landscape complexity can contribute to enhancing resilience to climate-change-induced weather events. To accomplish this, we construct a county-level panel dataset with rich information on landscape complexity, weather-related crop insurance losses, and weather conditions for the 2008-2018 period. In particular, we collect information on two types of landscape complexity or diversity measures – compositional complexity and configurational complexity. Panel fixed effects (FE) models are the primary approach used to examine the effect of landscape complexity on crop insurance losses at the county-level. We believe that this estimation strategy allows us to sufficiently account for potential unobserved confounders (i.e., due mainly to time-invariant unobservables) and to reasonably identify the effects of landscape complexity on crop insurance losses due to extreme weather events. We will also conduct several robustness checks using alternative empirical specifications and estimation methods (e.g., a moment-based instrumental variable (IV) model, and another "external-IV-free" approach) as next steps.

As noted above, previous studies have examined the impact of landscape complexity on ecosystem services and environment-related outcomes (Swinton et al., 2007; McDaniel, Tiemann, and Grandy, 2014; Landis, 2017; Duarte et al., 2018; Larsen and McComb, 2021), as well as on crop productivity (Li et al., 2009; Burchfield, Nelson, and Spangler, 2019; Renard and Tilman, 2019; Nelson and Burchfield, 2021). However, to the best of our knowledge, no previous research has investigated how landscape complexity influences aggregate weather-specific crop insurance losses. Since crop insurance losses can be considered as a measure of production risk and resilience at the county-level (i.e., higher crop insurance losses is associated with higher risk or lower resilience), our study gives insights on whether landscape complexity reduces risk and improves resilience in the agricultural sector. We primarily contribute to the literature in this regard. To the best of our knowledge, our study is the first to empirically investigate whether increasing landscape complexity reduces weather-related production losses using long-term data across the US. Additionally, this study complements existing scientific studies that argue that increasing landscape complexity enhances resilience of agriculture to climate change. For example, Prokopy et al. (2020) suggest that increasing the diversity of agricultural systems at the landscape level can address climate variability and achieve sustainability goals.

The second main contribution of the current study is our use of a novel county-level data set that allows us to quantitatively analyze the relationship between landscape complexity and crop insurance losses over a wider geographical scope and over a longer time-series coverage. Much of the agronomic studies only focus on crop diversity issues and are typically conducted only for particular field locations and only for shorter time periods. Only a few studies have used county-level data rather than field-scale data for landscape complexity research (Burchfield, Nelson, and Spangler, 2019; Nelson and Burchfield, 2021) . Moreover, we contribute to the literature by being one of the first to leverage innovative sources of data to analyze the resilience effects of landscape complexity over time. Also, we are able to merge new publicly available crop insurance data with county-level landscape complexity data that allow us to examine the effects of landscape complexity on crop insurance losses due to specific extreme weather events.

Our empirical results show that counties with greater landscape compositional complexity (e.g., higher Shannon diversity index) and greater configurational complexity (e.g., lower largest patch index) tend to have lower crop insurance losses due to excess heat or excess moisture. These results underscore the potential of enhancing landcover complexity as a means to enhance resilience against extreme weather events (especially for excess heat and moisture events) and consequently better adapt to climate change. Given the belief that climate change will likely increase the frequency and magnitude of extreme weather events in the future, these findings have important policy implications, highlighting the need for support and investment in federal or state conservation programs that promote and enhance landscape diversity in rural areas.

2 Background

There are two common defining features of the landscape: landscape composition and landscape configuration. Landscape composition refers to the categories of landcover found on a landscape), and landscape configuration refers to the spatial organization of landcover categories (Nelson and Burchfield, 2021). As agricultural expansion and intensification have greatly changed landscape, agriculturally driven landscape transformation includes a reduction in landscape compositional complexity (i.e., the number and quantity of landcover categories on a landscape) and a reduction of landscape configurational complexity (i.e., how landcover categories are arranged on a landscape) (Fahrig et al., 2011; Meehan et al., 2011). Declining landscape complexity (i.e., both compositional complexity and configurational complexity) has been shown to generate many negative impacts on the ecosystem services related to agricultural production (e.g., water retention, pollination, pest management, and climate change) (Fahrig et al., 2011; Tiemann et al., 2015).

When considering landscape complexity metrics, there are many options that can be found in the literature (Turner, 1990; Schindler, Poirazidis, and Wrbka, 2008; Plexida et al., 2014). Different metrics have their distinct characteristics regarding sensitivity to scale and rare categories, as well as boundaries (Li and Wu, 2004; Plexida et al., 2014). In this study, we follow Nelson and Burchfield (2021) where they measured landscape compositional complexity using six metrics associated with the number or the predominance of landcover categories across a landscape. They are as follows: Shannon diversity index, Simpson diversity index, richness, Shannon evenness index, Simpson evenness index, and percentage natural cover. The detailed description of these metrics is presented in Table 1. Following Nelson and Burchfield (2021), we measure landscape configurational complexity using four metrics associated with the arrangement of landcover categories across the landscape (e.g., the size of landcover patches, shape of landcover patches or mixing of landcover categories across the landscape). The four metrics include mean patch area, largest patch index, contagion, and edge density. Table 1 also presents the detailed definition and description for each configurational complexity metric.

3 Data Description

3.1 Crop Insurance Losses

The panel data constructed for this study comes from multiple sources, which are discussed in turn below. As suggested in the previous section, we are interested in the effect of landscape complexity on weather-related crop insurance losses. The main dependent variable of interest is crop insurance losses due to a specific weather event (e.g., drought, excess heat, or excess moisture). The sources for the crop insurance loss data used in the study are from the US Department of Agriculture (USDA) Risk Management Agency (RMA) Summary of Business (SOB) and Cause of Loss (COL) databases.[1] The datasets are based on actual administrative information from all insurance policies handled by the federal crop insurance program through the years, instead of collecting data from farm surveys. Thus, we expect that there is less measurement error. We obtain the insurance data aggregated to the county-crop level from 2008-2018. The SOB data contain information on total indemnities,

[1]The county-level crop insurance data from SOB and COL can be obtained from the following two websites: https://www.rma.usda.gov/SummaryOfBusiness and https://www.rma.usda.gov/SummaryOfBusiness/CauseOfLoss.

liabilities, and insured acres without disentangling the particular weather-related cause of loss. The COL data contain indemnity amounts for specific causes of loss, such as those due to drought, excess heat, and excess moisture (among others). The COL data also have information on net determined acres, which refer to the number of acres with specific weather-related indemnities.

Our dependent variables are created by combining information from the COL and SOB data sets. We apply two measures of weather-related crop insurance losses: an "indemnity-based" measure and an "acre-based" measure. The "indemnity-based" crop insurance loss measure is represented by the loss cost ratio (LCR), which is calculated as the ratio of total indemnities due to a specific weather-related cause (i.e., payment to the insured due to losses caused by a specific weather event), over total liabilities (i.e., the total dollar amount of all insurance protection outstanding). The LCR measures the proportion of total possible payouts that are paid for a specific weather-related cause. The "acre-based" crop insurance loss measure is represented by the loss acres ratio (LAR), which is calculated as the ratio of acres with weather-related indemnities (i.e., acres with crop insurance losses due to a specific weather event) over the total insured acres at the county level.

3.2 Landscape Complexity Indexes

After compiling the crop insurance loss data, we then collect the data needed to construct several measures of landscape complexity, which is our main independent variable of interest. As we mentioned in the previous section, following Nelson and Burchfield (2021), we apply several metrics of landscape compositional and configurational complexity (see Table 1). We use the USDA National Agricultural Statistics Service (NASS) Cropland Data Layer (CDL) as our indicator of landcover. This dataset classifies landcover at a 30 m resolution nationwide from 2008 to present using satellite imagery and extensive ground truth data.[2] Given its relatively high resolution, full coverage and historical availability, it is the best available data

[2]The landscape indexes from the CDL data can be obtained through the *landscapemetrics* package in R (Nelson and Burchfield, 2021).

for understanding agriculture landcover across the US (Nelson and Burchfield, 2021).

We measure landscape compositional complexity using a set of six metrics (i.e., Shannon diversity index, Simpson diversity index, richness, Shannon evenness index, Simpson evenness index, and percentage natural cover) and measure configurational complexity using a set of four metrics (i.e., mean patch area, largest patch index, contagion, and edge density).[3] Our current analysis focuses on the Shannon diversity index as an index for compositional complexity and the largest patch index as an index for configurational complexity. The Shannon diversity index is a measure of the abundance and evenness of landcover categories. This index is sensitive to rare landcover categories and higher values indicate higher compositional complexity. The largest patch index is a measure of patch dominance representing the percentage of the landscape covered by the single largest patch. Higher values of the large patch index generally indicate lower configurational complexity (Nelson and Burchfield, 2021). All the other landscape complexity indexes listed in Table 1 will be applied for sensitivity analysis in our next steps.

3.3 Weather Variables

In addition to data on crop insurance losses and landscape complexity, we utilize several weather variables from the Parameter Regression Independent Slopes Model (PRISM) climate group to serve as controls in our empirical analysis. There are time-county varying observable factors that can influence landscape transformation. Consistent with the approach used in Schlenker and Roberts (2009), the following weather variables are utilized in our study: degree days for extreme heat ("heating degree days (HDD)"), degree days for moderate heat ("growing degree days (GDD)"), and precipitation. The two degree day measures provide information on the number of days a crop is exposed to certain temperature ranges. We follow the method in Schlenker and Roberts (2009) to calculate HDD and GDD. We use degree days above 29°C as the measure for extreme heat and between 10-29°C as

[3]The details of each landscape complexity metric are shown in Table 1 and described in the Background section.

the measure of moderate heat. These temperature cutoffs have been widely used in climate econometrics literature (Annan and Schlenker, 2015; Wang et al., 2021). The degree day measures are the sums of daily exposures over the May-September growing season. The precipitation variable represents the cumulative sum of precipitation received (in m) over the May-September growing season.

We merge the county-level aggregates of these weather variables together with crop insurance losses and landscape complexity measures to generate the panel data set used in this study (n = 29,486). Descriptive statistics of the main variables used in the empirical analysis are summarized in Table 2. Figures 1 and 2 present the spatial distribution of landscape complexity across counties in the US based on the two indexes (i.e., Shannon diversity index and largest patch index). Landscape complexity varies greatly in the spatial dimension. Compositional complexity tends to be higher in northern and southeastern regions. Configurational complexity tends to be higher in eastern regions than in the western regions.

4 Empirical Methods

For our main empirical specification, we employ a linear panel data model with county fixed effects. We separately regress drought, excess heat, and excess moisture-related crop insurance loss measures (LCR and LAR) on landscape complexity indexes, HDD, GDD, precipitation, precipitation squared, and an overall linear time trend. More formally, we estimate the following empirical specification:

$$Loss_{it} = \beta_0 + \beta_1 LC_{it} + \beta_2 W_{it} + \alpha_i + \lambda T_t + \varepsilon_{it} \tag{1}$$

where $Loss_{it}$ represents the LCR or LAR measures for a specific cause of loss (i.e., drought, excess heat, or excess moisture) in county i and year t, LC_{it} is one of the landscape complexity indicators (i.e., Shannon diversity index, or largest patch index), W_{it} is the set of weather variables (i.e., HDD, GDD, precipitation, precipitation squared), α_i represents county fixed effects, T_t is a linear time trend variable, and ε_{it} is the idiosyncratic error term. The coefficient of interest is β_1. Note that the weather variables used as controls are consistent with previous studies that analyze nonlinear effects of weather on crop yield outcomes (Schlenker and Roberts, 2006, 2009; Annan and Schlenker, 2015).

We mainly utilized a linear fixed effects (FE) regression model to estimate equation (1). Using this estimation strategy allows us to better account for potential unobserved confounders caused by unobserved linear-additive county-specific unobservables. For example, location-specific geographic conditions that are largely time-invariant, such as topography and soil type, would be likely correlated to crop insurance losses and landscape complexity. Furthermore, the time trend variable is included to capture unobserved technological growth over time. Additionally, standard error clustering by county can be regarded as robust to heteroscedasticity, and spatial correlation of the error terms across counties (Cameron, Gelbach, and Miller, 2011).

5 Results and Discussions

Results from linear panel FE regressions of crop insurance losses as functions of landscape compositional or landscape configurational complexity are presented in Tables 3 and 4. For the LCR runs, the parameter estimates for the Shannon diversity index variable indicate that counties with higher landscape compositional complexity, as reflected by a greater Shannon diversity index, have statistically lower LCR due to excess heat (at the 1% significance level). However, no statistically significant relationship is observed between landscape compositional complexity and LCRs associated with drought or excess moisture. For the LAR regressions, the estimated parameters indicate that counties with higher landscape compositional complexity have statistically lower LARs due to excess heat and excess moisture (at the 1% level of significance). However, there is no statistically significant relationship between landscape compositional complexity and drought-related LARs.

In Table 4, we examine the impact of landscape configurational complexity on weather-related crop insurance losses. Recall that we use the largest patch index as the main measure of configurational complexity, where higher values of this index means lower configurational complexity. Our analysis reveals that county-level landscape configurational complexity (i.e., the largest patch index) has a positive and statistically significant relationship with both LCR and LAR due to excess moisture. Specifically, counties with greater configurational complexity (e.g., lower largest patch index) tend to have a lower proportion of insured payment and acres with losses due to excess moisture. Conversely, counties with greater configurational complexity tend to have significantly larger LCR and LAR due to drought. This means that higher configurational complexity contributes to higher losses due to drought. However, we do not find any statistically significant effects of configurational complexity on LCR and LAR related to excessive heat.

These findings indicate that increasing compositional landscape complexity likely has more significant loss mitigation effects against excess heat and excess moisture events (like floods). While increasing configurational landscape complexity appears to have a greater impact only on mitigating losses associated with excess moisture events. Overall, our findings suggest that enhancing the complexity of landcover provides a potential way to bolster resilience to extreme weather events (especially for excess heat and moisture events) and adapt to climate change. Given the belief that climate change will likely increase the frequency and magnitude of extreme weather events in the future, this finding points to important policy implications in terms of justifying support for federal or state conservation programs aimed at maintaining or enhancing landscape diversity in rural areas.

The main findings presented above align with previous ecological and agronomic literature, which consistently indicates a positive correlation between landscape diversity and crop yields (Dainese et al., 2019; Grab et al., 2018; Martin et al., 2019; Burchfield, Nelson, and Spangler, 2019; Nelson and Burchfield, 2021). This relationship implies that increasing landscape diversity can enhance agricultural productivity and contribute to the resilience of farming systems in the face of climate shocks. Furthermore, our regression analysis strongly supports the notion that higher landscape compositional complexity can enhance farms' resilience against excess heat and excess moisture events, while increased configurational complexity is effective in mitigating excessive moisture events. This finding further reinforces the idea that enhancing the diversity of agricultural systems at the landscape level can help address challenges arising from climate variability (Prokopy et al., 2020). In addition, targeting specific types of landscape complexity (compositional complexity or configurational complexity) maybe useful when different regions are confronted with different types of extreme weather events (e.g., regions with more frequent occurence of excess moisture may benefit more from increasing compositional complexity).

Regarding the weather variables considered as controls, the estimated county-level effects align closely with expectations. Specifically, we observe a nonlinear effect of the degree days measures (i.e., crop growth requires a certain level of heat, up to a threshold, for optimal development. Beyond this threshold, damage to the crops occurs). In Tables 3 and 4, we find that increased incidence of extreme heat (i.e., higher HDD) tends to increase the drought and heat-related losses, whereas GDD has a negative and statistically significant estimated coefficient for the crop insurance losses due to all the three causes (i.e., moderate temperatures reduce extreme weather related losses). Concerning the precipitation variables, the parameters generally exhibit a "U-shaped" pattern of behavior. For instance, as precipitation increases from zero, excess moisture-related losses tend to decrease initially. However, after reaching a certain "turning point," higher levels of precipitation contribute to an increase in excess moisture-related losses.

6 Conclusions

This study examines the impact of landscape complexity on weather-related crop insurance losses. To achieve this objective, we construct a unique county-level panel dataset covering the period from 2008 to 2018. Our approach involves merging a novel county-level dataset on landscape complexity with publicly available crop insurance loss and weather data. Empirical analysis is conducted using linear panel fixed-effects models. The findings of our empirical analysis suggest that counties with greater landscape compositional complexity and greater configurational complexity tend to have lower crop insurance losses due to excess heat or excess moisture. These results underscore the potential of landscape complexity as a factor contributing to the mitigation of weather-related crop insurance losses. However, we did not find evidence that increasing compositional or configurational complexity will enhance drought resilience.

The findings from our study point to several policy implications. First, enhancing the complexity of land cover presents a promising strategy for bolstering resilience to extreme weather events and adapting to climate change. To achieve this, various measures can be considered, such as implementing cover crops, substituting input-intensive corn-soybean areas with perennial bioenergy crops, and adopting nutrient-saving practices targeted at less productive and highly vulnerable lands (Prokopy et al., 2020). Second, farmers play a crucial role in determining the composition of species within a landscape and deciding whether to actively pursue efforts to increase landscape complexity. Therefore, it is essential for governmental and non-governmental agencies to develop effective policies and supportive instruments that encourage farmers to contribute to landscape diversification. Third, government support for further research is needed to expand our understanding of the field-level impacts of landscape diversification on climate change and risk resilience, which can in turn provide valuable insights for both producers and policymakers, enabling them to make informed decisions.

While our research represents a step forward in understanding the relationship between landscape complexity and climate-related production losses, it is essential to acknowledge that this study is still ongoing, and there are several limitations and areas that warrant future investigation. First, although panel fixed effects models serve as our primary approach, effectively accounting for potential unobserved time-invariant confounding factors, we plan to conduct further robustness checks using alternative empirical specifications in the subsequent stages of this study. Second, our current analysis focuses on a single index for each of the two features of landscape complexity, namely compositional complexity and configurational complexity. To gain a more comprehensive understanding, we intend to examine the impact of landscape complexity on insurance losses by incorporating alternative indicators of landscape complexity, as outlined in Nelson and Burchfield (2021). Third, this paper specifically concentrates on crop insurance production loss data in the United States, which we believe provides a valid dataset enabling separate estimation of the effects of landscape complexity on losses attributed to specific weather events. However, we also recognize the importance of perhaps considering a county-level crop yield datasets (instead of crop insurance loss data) to gain further insights into the potential heterogeneity of landscape complexity effects yields conditional on different types of weather conditions. We leave all these suggested research directions in the subsequent phases of this study.

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Figure 1: Spatial variation in compositional complexity across counties in the United States. Values presented are the average across all years (2008-2018) for the Shannon diversity index

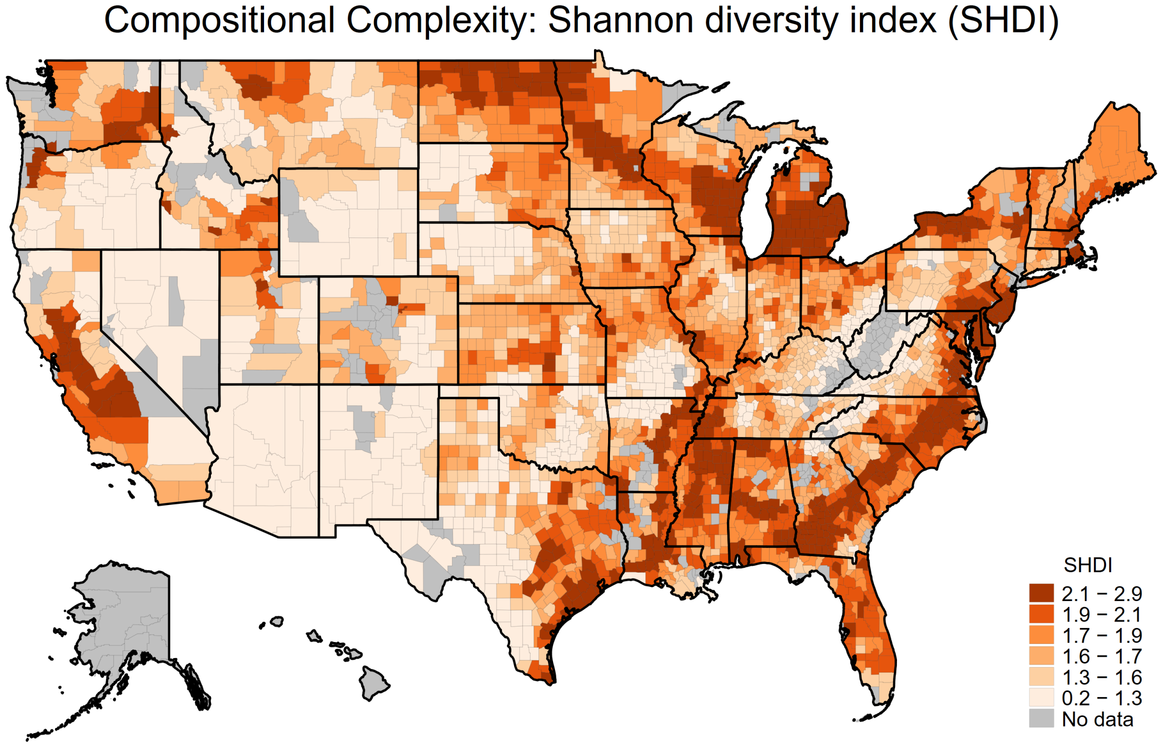

Figure 2: Spatial variation in configurational complexity across counties in the United States. Values presented are the average across all years (2008-2018) for the largest patch index

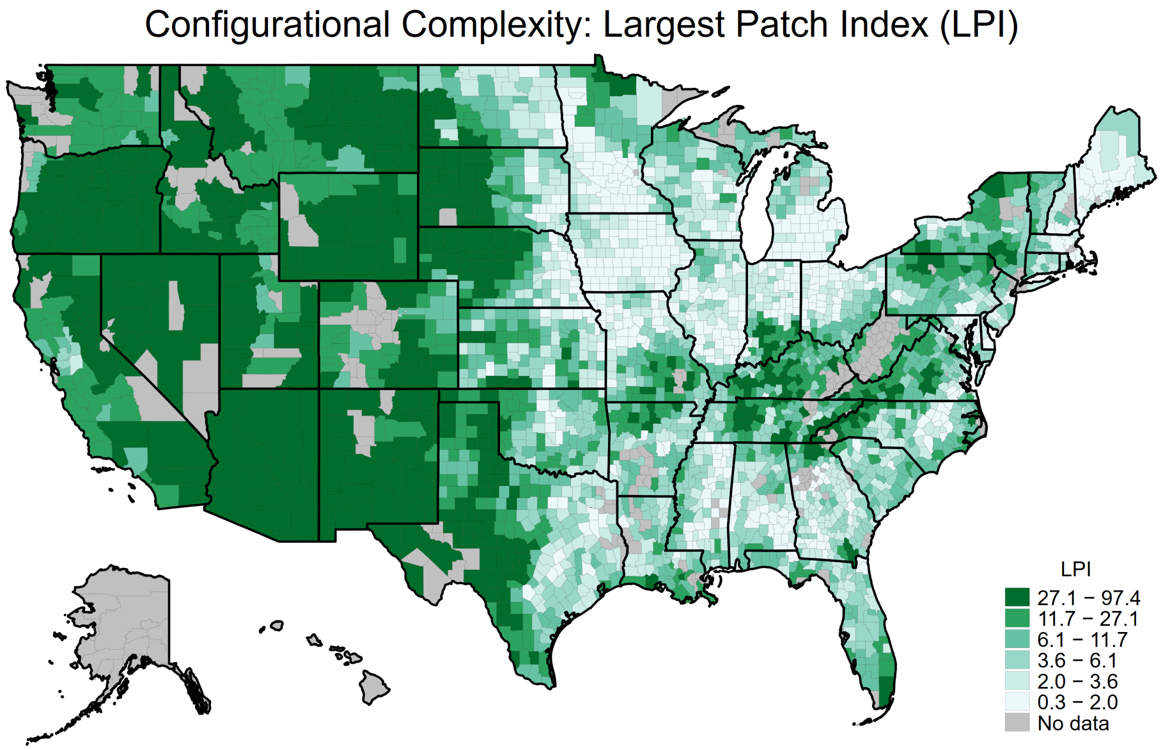

Table 1: Landscape Complexity Metrics

Type	Index	Description
Compositional complexity	Shannon diversity index	A measure of the abundance and evenness of landcover categories. This index is sensitive to rare landcover categories. Higher values indicate higher complexity.
	Simpson diversity index	A diversity measure that considers the abundance and evenness of landcover categories. This index is not sensitive to rare landcover categories. Higher values generally indicate higher complexity.
	Richness	A measure of the abundance of categories. Higher values generally indicate higher complexity.
	Shannon evenness index	A measure of diversity or dominance calculated as the ratio between the Shannon diversity index and the theoretical maximum of this index. Higher values generally indicate higher complexity.
	Simpson evenness index	A measure of diversity or dominance calculated as the ratio between the Simpson diversity index and the theoretical maximum of this index. Higher values generally indicate higher complexity.
	Percentage natural cover	A simple measure of the predominance of undeveloped landcovers on a landscape. Higher values generally indicate lower complexity.
Configurational complexity	Mean patch area	A measure of patch structure. Higher values generally indicate lower complexity.
	Largest patch index	A measure of patch dominance representing the percentage of the landscape covered by the single largest patch. Higher values generally indicate lower complexity.
	Contagion	A measure of dispersion and interspersion of landcover classes where a high proportion of like adjacencies and an uneven distribution of pairwise adjacencies produces a high contagion value. Higher values generally indicate lower complexity.
	Edge density	A measure of the patchiness of the landscape. Higher values generally indicate higher complexity.

Note: This table of landscape complexity metrics follows Nelson and Burchfield (2021).

Table 2: Descriptive Statistics

Variable	Description	Obs	Mean	St. Dev.	Min	Max
LCR_drought	Drought-related LCR for all insured crops (%)	29,486	3.77	9.38	0.00	100.00
LCR_heat	Excess-heat-related LCR for all insured crops (%)	29,464	0.40	1.86	0.00	78.40
LCR_moisture	Excess-moisture-related LCR for all insured crops (%)	29,464	2.34	5.14	0.00	98.91
LAR_drought	Drought-related LAR for all insured crops (%)	29,486	7.08	13.76	0.00	100.00
LAR_heat	Excess-heat-related LAR for all insured crops (%)	29,458	0.75	2.79	0.00	92.03
LAR_moisture	Excess-moisture-related LAR for all insured crops (%)	29,486	5.95	10.29	0.00	100.00
Shannon Diversity Index	One of landscape compositional complexity indexes	29,486	1.71	0.42	0.04	3.03
Largest Patch Index	One of landscape configurational complexity indexes	29,486	13.79	18.63	0.22	99.56
HDD	Heating degree days (Celsius degree)	29,486	73.22	81.36	0.00	894.39
GDD	Growing degree days (Celsius degree)	29,486	2248.32	537.09	873.26	3500.94
Precipitation	Precipitation (mm)	29,486	574.64	228.45	2.39	1873.07

Table 3: The Effect of Landscape Compositional Complexity (Shannon Diversity Index) on Crop Insurance Loss

Variable	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Shannon Diversity Index	0.307	-0.867***	-1.114	-0.969	-2.001***	-3.178***
	(0.743)	(0.189)	(0.742)	(1.175)	(0.269)	(1.089)
HDD	0.091***	0.015***	0.001	0.087***	0.020***	0.007***
	(0.004)	(0.001)	(0.001)	(0.005)	(0.002)	(0.002)
GDD	-0.003***	0.001***	-0.001**	0.007***	0.001***	-0.003***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Precipitation	-0.043***	-0.001***	0.009***	-0.063***	-0.001	0.017***
	(0.002)	(0.000)	(0.001)	(0.003)	(0.001)	(0.002)
Precipitation^2	0.000***	0.000**	0.000*	0.000***	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Trend Control	Yes	Yes	Yes	Yes	Yes	Yes
Observation	29,486	29,464	29,464	29,486	29,458	29,486

Notes: (i) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (ii) Standard errors are in parentheses.

Table 4: The Effect of Landscape Configurational Complexity (Largest Patch Index) on Crop Insurance Loss

Variable	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Largest Patch Index	-0.101***	0.001	0.026***	-0.121***	0.003	0.058***
	(0.015)	(0.003)	(0.006)	(0.019)	(0.004)	(0.010)
HDD	0.091***	0.015***	0.001	0.087***	0.021***	0.008***
	(0.004)	(0.001)	(0.001)	(0.005)	(0.002)	(0.002)
GDD	-0.003***	0.001***	-0.001***	0.007***	0.001***	-0.003***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Precipitation	-0.042***	-0.001***	0.008***	-0.063***	-0.001	0.016***
	(0.002)	(0.000)	(0.001)	(0.003)	(0.001)	(0.002)
Precipitation^2	0.000***	0.000**	0.000*	0.000***	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Trend Control	Yes	Yes	Yes	Yes	Yes	Yes
Observation	29,486	29,464	29,464	29,486	29,458	29,486

Notes: (i) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (ii) Standard errors are in parentheses.