Landscape Complexity Mitigates Weather-Related Crop Insurance Losses and Enhances Climate Resilience

Yuyuan Che
Assistant Professor, Department of Agricultural and Applied Economics, Texas Tech University. Email: yuyuan.che@ttu.edu

Serkan Aglasan
Assistant Professor, Department of Agricultural and Resource Economics, University of Arizona. Email: serkanaglasan@arizona.edu

Emily K. Burchfield
Associate Professor, Department of Environmental Sciences, Emory University. Email: emily.burchfield@emory.edu

Roderick M. Rejesus
Professor & Extension Specialist, Department of Agricultural and Resource Economics, North Carolina State University. Email: rmrejesu@ncsu.edu

Acknowledgments
We would like to acknowledge the feedback from participants at the 2023 AAEA Meetings and the 2024 SCC-76 Meetings. The work of Rejesus on this manuscript was supported in part by USDA NIFA Hatch Project No. NC02959 (Risk and Resilience Implications of Crop Insurance and Agricultural Technologies). The authors declare no financial relationships or other potential conflicts of interest related to this research.

Landscape Complexity Mitigates Weather-Related Crop Insurance Losses and Enhances Climate Resilience

Abstract

This study explores whether increasing landscape complexity reduces weather-related crop insurance losses and improves farm resilience in the United States (US). Using 2008-2018 county-level panel data on landscape complexity, insurance losses, and weather variables, we estimate fixed-effects models with multiple robustness checks, including fractional regression and "external-instrument-free" approaches. Results show that counties with greater landscape complexity tend to have lower crop insurance losses from drought, excess heat, and excess moisture, particularly for drought and heat. These findings suggest that increasing landscape complexity can improve farm resilience to extreme weather events and facilitate climate change adaptation in the US agricultural sector.

Keywords: climate change, ecosystem service, landscape diversity, weather resilience

JEL classification: Q10, Q15, Q18, Q54, Q57

1. Introduction

A large and growing body of literature has documented the substantial negative impacts of climate change on agricultural crop production (Tack et al., 2015; D'Agostino and Schlenker, 2016; Wang et al., 2021), with over 31% of historical crop yield losses in the United States (US) attributed to droughts, extreme heat, and excess moisture events (Skees et al., 2008). Scientific studies suggest that the frequency of excessive heat, drought, and heavy precipitation events is increasing due to climate change (Stocker, 2014; Cook et al., 2015). These changes are of significant concern to agriculture, which relies heavily on stable and favorable weather patterns for good yields and profitability. 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.

Landscapes with higher levels of diversity and complexity have been shown to provide multiple ecosystem services essential to agricultural production and enhance agricultural resilience to changing climate patterns (Gaudin et al., 2015; Verhagen et al., 2016; Duarte et al., 2018; Renard et al., 2023). Specifically, diverse landscape compositions enhance nutrient cycling, improve soil health, boost pollination services, and increase economic resilience to climate stress (Altieri et al., 2011; Abson et al., 2013; Tiemann et al., 2015; Christman et al., 2024; Fabri et al., 2024). Moreover, complex landscape configuration has been shown to influence water quality and pollination benefits, and the spatial arrangement of land cover can affect nutrient and sediment retention while mitigating the impacts of extreme moisture events such as flooding (Verhagen et al., 2016). Therefore, increasing landscape complexity becomes significant for improving ecological processes that bolster agricultural resilience, especially in light of the anticipated adverse impacts of climate change on agricultural production.

This study addresses the question of whether increasing landscape complexity can help mitigate weather-related production losses and strengthen the resilience of farms in the US. 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, or excess moisture.[1] Hence, this study aims to assess whether enhancing landscape complexity through increasing habitat diversity (e.g., incorporating a greater variety of crop types) or reducing monocultures (e.g., promoting crop rotation or intercropping) can contribute to improving 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. 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 also conduct several robustness checks using alternative empirical specifications and estimation methods to account for various econometric issues that may influence the precision of our parameters of interest (i.e., a fractional regression approach, two "external-instrument-free" estimation procedures, and a variety of alternative empirical specifications).

A rich literature has already demonstrated that greater landscape complexity increases the provision of ecosystem services critical to agricultural resilience under changing climatic

[1] Drought as a cause of loss generally refers to a prolonged period of below-average precipitation leading to a lack of soil moisture. A drought can cause crop damage through lack of water even if temperatures are not excessively high. Excess heat, on the other hand, specifically indicates extreme high temperatures that can stress and damage crops even with available soil moisture. Losses due to excess moisture are generally those due to flood events.

conditions (e.g., Reidsma and Ewert, 2008; Ricketts et al., 2008; Termorshuizen and Opdam, 2009; Abson et al., 2013; Bastian et al., 2014; McDaniel et al., 2014; Gaudin et al., 2015; Isbell et al., 2015; Verhagen et al., 2016; Schulte et al., 2017; Duarte et al., 2018; Antolini et al., 2020; Renard et al., 2023; Fabri et al., 2024). For example, there is evidence that greater crop diversity and diverse rotations improve yield stability under drought and heat stress (Reidsma and Ewert, 2008; Gaudin et al., 2015; Isbell et al., 2015; Renard et al., 2023), while increased vegetative complexity, such as through crop diversification, cover cropping, and riparian buffers, mitigates the effects of excessive moisture and flooding (Schulte et al., 2017; Antolini et al., 2020). Beyond these documented direct agronomic benefits, increasing landscape complexity has also been shown to promote key ecosystem processes such as nutrient retention, pollination, pest management, and soil health that collectively support more resilient farming systems (Ricketts et al., 2008; McDaniel et al., 2014; Verhagen et al., 2016), potentially reducing income risk and improving long-term economic returns (Abson et al., 2013; Fabri et al., 2024).

Despite the evidence linking landscape complexity to enhanced climate resilience through ecosystem services, which are largely from agronomic and ecological studies, there has been limited empirical examination of how these benefits translate into reduced weather-specific production losses at broader spatial scales. We contribute to the literature in this regard. To the best of our knowledge, our study is the first to rigorously investigate whether increasing landscape complexity decreases weather-related crop insurance losses using long-term data across the US. By considering crop insurance losses as a measure of production risk and resilience (i.e., higher crop insurance losses are associated with higher risk or lower resilience), our analysis provides valuable insights into how landscape heterogeneity may lower vulnerability to adverse weather events and stabilize agricultural returns in the face of climate

extremes. In addition, our study complements existing ecological studies that suggest that landscape complexity can bolster ecosystem services, which in turn enhances resilience to extreme weather events. For example, greater crop diversity in US counties has been shown to reduce drought- and heat-related losses, as a more varied range of crops increases the likelihood of including drought-resistant species and lowers the overall sensitivity of the most abundant crops to these extremes (Renard et al., 2023). Previous studies also suggest that implementing practices that enhance landscape complexity, such as cover cropping, riparian buffers, and prairie strips, can significantly reduce excess moisture damage by decreasing water runoff, increasing soil and nutrient retention, and supporting greater insect, pollinator, and bird diversity (Schilling et al., 2014; Kelly et al., 2017; Schulte et al., 2017; Dalzell and Mulla, 2018; Antolini et al., 2020).

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 (i.e., the whole continental US) and over a longer time-series coverage (i.e., 2008-2018), which in turn enhances the external validity of our findings. Much of the existing agronomic and ecological studies that explore how landscape complexity affects ecosystem services and agricultural resilience are typically limited to specific field locations and short time periods, which might constrain their external validity. Only a few studies have used county-level data rather than field-scale data to examine landscape complexity in the context of agricultural production (e.g., Burchfield et al., 2019; Nelson and Burchfield, 2021). However, these studies do not explicitly analyze the role of landscape complexity in enhancing climate resilience. Our research contributes 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. 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., more variation in land cover and crop types) tend to have lower crop insurance losses due to drought, excess heat, or excess moisture (with more consistent estimated effects for heat-related losses). In addition, counties with greater configurational complexity (e.g., more complex spatial arrangement of land cover) tend to incur fewer crop insurance losses from excess heat. These results underscore the potential of enhancing land cover complexity as a means to enhance resilience against extreme weather events (i.e., especially heat-related 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

A landscape can typically be characterized by two key features: landscape composition and landscape configuration. Landscape composition refers to the variety and types of land cover present within a given area, essentially representing the different categories of land use or natural features within the landscape. Landscape configuration, in contrast, describes the spatial arrangement or organization of these land cover categories, indicating how different types of land cover are distributed across the landscape (Nelson and Burchfield, 2021). Landscape complexity includes compositional complexity and configurational complexity. Specifically, landscape compositional complexity refers to the diversity and abundance of different land cover

categories, while landscape configurational complexity relates to the pattern and distribution of these categories within the landscape (Fahrig et al., 2011; Meehan et al., 2011). Agricultural expansion and intensification have significantly altered landscapes over time, leading to transformations primarily driven by agricultural activities (Landis, 2017). This transformation is often associated with a decline in both the compositional and configurational complexity of the landscape. The change in landscape complexity has been shown to have significant impacts on ecosystem services that are critical to agricultural production (Termorshuizen and Opdam, 2009; Bastian et al., 2014; Duarte et al., 2018).

There is a large amount of literature supporting the idea that increased landscape compositional complexity improves a variety of ecosystem services relevant to food production in agroecosystems. For example, greater landscape diversity enhances nutrient recycling, regulates local hydrological processes, improves pest management, and facilitates the detoxification of noxious chemicals (Altieri, 1999; Altieri et al., 2011). Furthermore, increases in landscape diversity boost belowground soil health, which is associated with increases in soil aggregation, organic carbon, total nitrogen, microbial activity, and decreases in the carbon-to-nitrogen acquiring enzyme activity ratio (McDaniel et al., 2014; Tiemann et al., 2015). All of these factors help boost crop production. Likewise, increases in landscape diversity improve pollination activity, which in turn benefit yields (Ricketts et al., 2008; Klein et al., 2009; Grab et al., 2019; Vasiliev and Greenwood, 2020; Christman et al., 2024). By welcoming beneficial insects, increased landscape diversity is even associated with reduced pesticide use (Gardiner et al., 2009; Rusch et al., 2016; Hatt et al., 2018). Beyond these ecological benefits, increased compositional complexity has been shown to enhance economic resilience to weather stress (Abson et al., 2013; Fabri et al., 2024).

Landscape configurational complexity affects ecosystem service capacity through the location of specific land cover types, the use and structure of landscape patches, and the presence of linear elements like hedgerows and prairie strips (Ricketts et al., 2008; Veres et al., 2013; Verhagen et al., 2016; Schulte et al., 2017; Yang et al., 2019). There is particularly strong evidence that these spatial arrangements influence nutrient retention (Liu et al., 2012; Bateni et al., 2013; Sun et al., 2013), pollination services (Nicholson et al., 2017; Grab et al., 2019; Nottebrock et al., 2022; Christman et al., 2024), sediment retention (Lenka et al., 2012; Yang et al., 2012; Shi et al., 2013), and flood control (Mayor et al., 2011; Sriwongsitanon and Taesombat, 2011; Lenka et al., 2012; Schilling et al., 2014; Von Freyberg et al., 2014). For example, the placement and connectivity of particular land cover types can enhance pollination by shaping foraging behavior, while the strategic location of vegetation can improve nutrient and sediment retention. Especially, the flood control findings are relevant: the presence of trees, shelterbreaks, and other linear elements in upstream areas can substantially reduce runoff into downstream agricultural fields, thereby mitigating flood risks and enhancing overall ecosystem service capacity (Marshall et al., 2009; Borin et al., 2010).

To empirically assess landscape complexity, researchers commonly rely on a set of landscape metrics that quantify both compositional and configurational dimensions (Turner, 1990; Schindler et al., 2008; Plexida et al., 2014). For landscape composition, the Shannon diversity index (SDI) is widely employed.[2] This index accounts for the number and relative abundance of different land cover categories, providing a robust measure of overall landscape diversity (Aguilar et al., 2015; Nelson and Burchfield, 2021). Higher SDI values, typically ranging from about 1.5 to 3, indicate a more complex and diverse landscape. In contrast,

[2] SDI is typically calculated using the following formula: $SDI = -\sum_{i=1}^{k} p_i \cdot ln(p_i)$ where p_i is the proportion of the landscape occupied by patch type i across all k patch types. Higher values indicate higher complexity.

configurational complexity is often assessed through metrics such as mean patch area (MPA).[3] By reflecting the average size of land cover patches, MPA can offer insight into how finely grained or coarsely aggregated a landscape's structure is (Nelson and Burchfield, 2021). Higher MPA values generally signal more homogeneity, thus lower configurational complexity, while smaller, more numerous patches signify a more spatially complex arrangement.

Figure 1 presents a set of examples for low and high compositional complexity (SDI) (Maps C and D) and another for low and high configurational complexity (MPA) (Maps A and B). Map C (lower left quadrant) depicts a county with low compositional complexity given that the map only has one predominant land use as reflected in the predominantly red grids. On the other hand, Map D reflects a county with higher compositional complexity since there is a variety of land uses in the area as depicted by the numerous colors on the map representing various land uses. Lower configurational complexity is shown in Map A (top left quadrant), and it reflects more landscape complexity since there are a lot more "finely grained" smaller land use patches with various colors (i.e., smaller sized patches with more fragmented land uses). In contrast, Map B (top right quadrant) has larger, coarser patches with only yellow and green colors (that represent more homogeneous land uses). Hence, a larger valued mean patch area suggests lower landscape complexity.

3. Data description

The panel data constructed for this study comes from multiple sources, which are discussed 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

[3] MPA is calculated as follows: $MPA = \frac{\sum_{i=1}^{k} A_k}{k}$ where A_k is the area of the i^{th} patch and k is the number of patches for which the mean is being computed in the landscape. This value approaches zero if all patches are small and numerous (more complexity). MPA increases as the patch areas increase (i.e., lowering complexity).

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.[4] 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 level from 2008-2018 for the whole continental US. The SOB data contain information on total indemnities, 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 datasets (Aglasan et al., 2024; Won et al., 2024). 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) (Aglasan et al., 2023). 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

[4] The county-level crop insurance data from SOB and COL can be obtained from the following two websites: https://www.rma.usda.gov/tools-reports/summary-of-business/state-county-crop-summary-business and https://www.rma.usda.gov/tools-reports/summary-business/cause-loss.

(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.

In the COL data, it is crucial to acknowledge that the weather-related cause linked to a particular indemnity payment relies on the judgment of crop insurance adjusters and the information provided by producers, which may not always precisely match the actual cause of loss (Perry et al., 2020). When adjusters decide that indemnities should be issued, they assign a cause to the loss based on factors such as historical weather patterns, the timing of the event, and details provided by the producer (Perry et al., 2020). However, in some cases, the selected cause may not fully represent the true reason, or the loss may have been caused by multiple factors, making it challenging to attribute the loss to a single cause. This is one reason why we incorporate weather variables as controls in our empirical model, as discussed later. Nonetheless, the determinations made by adjusters and producers remain a valuable and generally reliable measure of weather-related losses in US agriculture.

After compiling the crop insurance loss data, we collect data needed to construct the main measures of landscape complexity, which is our main independent variable of interest. As we mentioned in the previous section, we utilize the Shannon diversity index (SDI) to measure landscape compositional complexity and mean patch area (MPA) to measure configurational complexity for agricultural land use in the continental US. Specifically, we use the USDA National Agricultural Statistics Service (NASS) Cropland Data Layer (CDL) as our indicator of land cover (and as basis for calculating SDI and MPA). This dataset classifies land cover at a 30 m resolution nationwide using satellite imagery and extensive ground truth data.[5] Given its

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

relatively high resolution, full coverage and historical availability, it is the best available data for understanding agriculture land cover across the US (Nelson and Burchfield, 2021).

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 ℃ as the measure for extreme heat and between 10-29 ℃ as 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 mm) over the May-September growing season.

We merge the county-level aggregates of these weather variables, crop insurance losses, and landscape complexity measures to generate the baseline panel data set used in this study (i.e., covering the continental US from 2008-2018). Descriptive statistics of the main variables used in the empirical analysis are summarized in Table 1. Figure 2 presents the spatial distribution of landscape complexity across counties in the US based on the two indexes (i.e., SDI and MPA). Landscape complexity varies greatly in the spatial dimension. Compositional complexity is generally higher in the northwest, southeast, and western (e.g., California) regions, while less

configurational complexity (i.e., higher MPA values) is more prominent in the central region of the US.

4. Empirical methods

4.1 Baseline specification and estimation strategy

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 (i.e., 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:

$$Loss_{it} = \beta_1 LC_{it} + \boldsymbol{W_{it}\beta_2} + \lambda t + \alpha_i + \varepsilon_{it} \quad (1)$$

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., SDI or MPA), $\boldsymbol{W_{it}}$ is the set of weather variables (i.e., HDD, GDD, precipitation, precipitation squared), t is a linear time trend variable, α_i represents county fixed effects, 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 the nonlinear effects of weather on crop yields (Schlenker and Roberts, 2006, 2009; Annan and Schlenker, 2015).

Considering the panel nature of our dataset, we first utilize a traditional linear panel fixed effects (FE) 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 both the dependent variable (crop insurance losses) and the main independent variable of interest

(landscape complexity). However, because soil quality measures (such as soil organic matter or soil organic carbon) do not vary significantly from year to year (Post and Kwon, 2000; Wuest, 2014), the heterogeneous soil quality across counties can reasonably be treated as time-invariant. Consequently, any potential endogeneity arising from these factors is likely absorbed by the county-fixed effects. Furthermore, the time trend variable is included to capture unobserved technological growth over time. To facilitate proper inference, we also use standard errors clustered by county to account for heteroskedasticity and potential year-to-year correlations within a county (Cameron et al., 2011).

4.2 Robustness checks: Alternative specifications

To assess the robustness of the baseline linear fixed effects (FE) model in Equation (1), we estimate several alternative empirical specifications: (i) We include both landscape complexity indexes (SDI and MPA) into a single model for each of our insurance loss variables. (ii) We incorporate state-specific trend variables in addition to the general linear time trend. (iii) We include a measure of irrigation use at the county level. (iv) We extend the analysis to only consider counties east of the 100th meridian where farming is predominantly non-irrigated. (v) We incorporate year-fixed effects in our model rather than relying on a general time trend variable. (vi) We incorporate the shares of corn, soybeans, and wheat among total planted acres as three additional control variables. We also estimate how landscape complexity affects crop insurance losses attributable to specific weather events for selected major crops (corn, soybeans, and wheat).

The alternative empirical specifications considered above serve as robustness checks for several reasons. First, we include two landscape indexes (SDI and MPA) in a single regression to prevent omitted variable bias and provide a clearer picture of how landscape complexity

influences weather-related crop insurance losses. Since SDI and MPA have the potential to be correlated with the unobserved error term when only one and not the other is included in the specification. That is, not including both complexity measures can potentially obscure each metric's true impact. Including both SDI and MPA together not only captures each index's distinct contribution to climate resilience (e.g., reduced insurance losses) but also allows us to examine whether higher landscape compositional complexity (SDI) exerts an effect apart from the influence of landscape configurational complexity (MPA).

Second, incorporating state-specific trends accounts for differential temporal shocks across states (Xu et al., 2013). Third, because irrigation may influence the likelihood and magnitude of crop insurance losses, we introduce an irrigation variable into Equation (1) to sharpen identification. However, this approach carries potential drawbacks, as some researchers may argue that such controls could be endogenous "bad controls," potentially adding noise to the estimation. Fourth, we extend our analysis to only consider counties east of the 100th meridian, where farming is predominantly non-irrigated (Annan and Schlenker, 2015), to provide a useful contrast to the base model for the whole US, as irrigation generally does not typically play a significant role in this region. Fifth, incorporating year-fixed effects further refines our model by flexibly controlling for temporal shocks and macro-level conditions that affect all counties equally. This adjustment helps separate the influence of landscape complexity from broader annual shocks such as major shifts in commodity markets, policy changes, or widespread climatic anomalies, thus ensuring that our estimates more accurately reflect the true relationship between landscape complexity and crop insurance losses.

Finally, we add the shares of major crops (corn, soybeans, and wheat) among planted acres for all crops as three control variables to better capture farmers' adaptive decisions and reduce

potential omitted variable bias. By including the proportions of these crops, we can identify whether observed changes in weather-related insurance losses are driven by strategic shifts to particular high- or low-water-demand crops rather than by overall landscape diversity alone. This approach prevents us from over-attributing losses to SDI and MPA when crop choice adaptation may be at play, thereby allowing us to more clearly differentiate between the effects of crop choices and landscape structure changes. Also, the effects of landscape complexity on insurance losses may vary across crops, thus, we conduct additional separate estimations for the following major commodities: corn, soybeans, and wheat.

4.3 Robustness checks: Alternative estimation procedures

In addition to the traditional linear FE estimation, we apply three alternative estimation strategies to assess the robustness of the baseline model results. The first is a fractional regression approach for unbalanced panel data, and the other two are recently developed "external-instrument-free" instrumental variable (IV) methods (i.e., one by Lewbel (2012) and the other by Kiviet (2013, 2020)). The fractional regression technique accounts for the fractional nature of the dependent variable, while the two external-instrument-free procedures can help further address identification issues by dealing with possible residual endogeneity due to time–county varying unobservables.

Our primary estimation method, the traditional linear panel FE model, has the advantage of accounting for time-invariant unobservables. However, it does not adequately handle fractional outcomes since our dependent variables (i.e., LCR and LAR) are bounded between zero and one. This raises the concern that the fractional nature of these variables may require a different estimation technique, as the linear FE model could produce predictions outside the [0,1] range. To address these concerns, we perform a robustness check by estimating Equation (1) using the

fractional regression method for unbalanced panel data, as developed by Wooldridge (2019). This method also referred to as the correlated random effects (CRE) probit model, is similar to the linear panel FE model in that it accounts for potential endogeneity due to unobserved heterogeneity. However, it offers the additional advantage of accounting for the nonlinear characteristics of fractional outcomes through quasi-maximum likelihood (QML) techniques, with specific link functions such as probit or logit. Wooldridge's approach builds on the Mundlak-Chamberlain framework, which controls for unobserved heterogeneity by modeling county fixed effects as a linear function of the county-level averages of the covariates (Mundlak, 1978). This method further adjusts for unobserved heterogeneity in fractional response models by incorporating the time-averaged covariates and accounting for the varying number of time periods available across cross-sectional units.

In addition, we employ a moment-based instrumental variable (IV) procedure, also known as a heteroskedasticity-based IV, as an additional robustness check (Lewbel, 2012). While we believe that the inclusion of county fixed effects and time trends in Equation (1) likely captures the major sources of potential endogeneity, there may still be unobserved factors varying across both time and space that could threaten the model's identification. For example, unobserved variations in cooperative extension efforts across time and counties could affect both landscape complexity and crop insurance losses. Although the linear FE and CRE probit methods discussed earlier have their own advantages given the panel nature of the data and/or fractional outcome, they do not fully address the potential residual endogeneity caused by time-and county-varying unobservables. Traditional IV methods, such as two-stage least squares (2SLS), are typically used to control for unobserved variables that vary over time and across counties and potentially affect both the outcome and the main independent variable. However, we lack suitable external

instruments that are correlated with the potentially endogenous independent variable (landscape complexity indicator) and uncorrelated with the dependent variables (LCR or LAR), thereby violating the exclusion restrictions required for traditional IV methods. To overcome this limitation, we use a moment-based IV approach that does not require external instruments (i.e., an "external-instrument-free" approach) (Lewbel, 2012).

The moment-based IV estimator developed by Lewbel (2012) exploits heteroscedasticity in the error terms of the first-stage regressions (e.g., the regression of the potentially endogenous variable on the observable covariates) to identify the coefficients of the endogenous variables in the main equation, even in the absence of valid external instruments. According to Lewbel (2012), identification is achieved if the error terms in the first-stage regression (i.e., landscape complexity as a function of exogenous variables in the main equation) exhibit heteroscedasticity, and a subset or all of the exogenous variables in the second-stage equation are uncorrelated with the covariance between the error terms in the first and second stages (i.e., Equation (1)). In this case, the residuals from the first-stage regression, multiplied by the mean-centered exogenous covariates, serve as valid instruments.

Formally, with Equation (1) as the main estimating equation and the landscape complexity variable as the potentially endogenous variable, the first-stage regression in the Lewbel (2012) approach is:

$$LC_{it} = \boldsymbol{X_{it}}\boldsymbol{\theta} + \mu_{it}, \tag{2}$$

where $\boldsymbol{X_{it}}$ represents all the exogenous variables. Lewbel (2012) has shown that $(\boldsymbol{X_{it}} - \overline{\boldsymbol{X}})\hat{\mu}_{it}$ can be used as a valid IV in a standard 2SLS approach if there is heteroscedasticity in Equation (2) (i.e., $Cov(\boldsymbol{X_{it}}, \mu_{it}^2) \neq 0$). To confirm the presence of heteroscedasticity, we employ the Breusch-Pagan (BP) test (Breusch and Pagan, 1979). The BP test rejects the null hypothesis of

homoscedasticity (i.e., BP test statistic is 2592.35 and the p-value is 0.000) when estimating the effect of SDI on insurance losses. The test result above supports the use of the moment-based IV approach by Lewbel (2012) as an alternative estimation strategy to address residual endogeneity due to time- and county-varying unobservables.

In addition to the Breusch-Pagan (BP) test, we conduct a series of diagnostic tests to evaluate the validity and strength of the Lewbel (2012) IV approach.[6] First, we employ the Kleibergen-Paap rk LM test statistic to assess potential underidentification in the IV model (Kleibergen and Paap, 2006). The resulting test statistics and corresponding p-values suggest that we can reject the null hypothesis of underidentification. Second, we examine the strength of the instruments using the Kleibergen-Paap rk Wald F statistic. These tests indicate that we can reject the null hypothesis that the IVs used are weak. Finally, we apply the Hansen J test to evaluate the overall validity of IVs. Across all model specifications, the Hansen J test statistics are large (e.g., all exceeding 110) with p-values below 0.01. These suggest that one can reject the null hypothesis that all IVs used in the moment-based IV procedure are valid (i.e., this means that at least one IV used in the estimation is not valid). Nevertheless, as noted by Baum and Lewbel (2019), it is possible for the Hansen J test to fail to support the validity of all IVs used, but the key assumptions for the moment-based IV model to work can still hold in general. Given that the majority of diagnostic tests support the appropriateness of the Lewbel (2012) IV approach, we retain this method as a robustness check in our empirical analysis.

To further validate our results from the linear fixed-effects (FE) and Lewbel (2012) moment-based IV approaches, we also employ a recently developed "external-instrument-free" estimation method, known as the "kinky least squares" (KLS) regression proposed by Kiviet

[6] All diagnostic test statistics are presented in Table 5.

(2013, 2020). Similar to Lewbel's approach, the KLS method addresses potential residual endogeneity arising from time-county-varying unobservables, but it does so without relying on external instruments. We also argue that the endogeneity correlations are positive in our context such that the potentially endogenous landscape complexity variable is likely positively correlated with the residual time-county-varying unobservables in the error term (i.e., unobserved extension or outreach effort that may be positively correlated with landscape complexity).[7]

The KLS approach establishes assumptions about the permissible degree of endogeneity within the model and achieves set identification of the coefficients by constraining endogeneity correlations within specified bounds. By selecting a range of endogeneity correlation values, the researcher can generate sets of coefficient estimates that reflect the assumptions made about the underlying level of endogeneity. Kripfganz and Kiviet (2021) suggest that asymptotically conservative inference can be performed by considering the union of confidence intervals over a grid of such endogeneity correlations (e.g., 0.1, 0.2, 0.3, and so forth). Thus, we estimate the KLS model at assumed endogeneity correlations ranging from 0 to 1 in 0.1 increments when including the Shannon diversity index.[8] If the KLS estimates at small to moderate levels of assumed endogeneity (e.g., say, between 0.1 and 0.4) remain consistent with our baseline linear FE results, this suggests that our baseline findings are generally robust. In other words, a small to moderate degree of residual endogeneity does not alter the key inferences drawn from the linear FE model. Thus, if modest levels of assumed endogeneity fail to overturn our baseline conclusions, we have greater confidence in the overall robustness of our results.

[7] Specifically, Shannon diversity index is likely positively correlated with the residual time-county-varying unobservables in the error term, whereas the mean patch area is likely negatively correlated with these unobservables. Because a higher Shannon diversity index indicates greater landscape compositional complexity, while a lower mean patch area signifies reduced landscape configurational complexity.

[8] We estimate the KLS model at assumed endogeneity correlations ranging from 0 to -1 in -0.1 increments when including the mean patch area variable.

5. Results and discussions

5.1 Baseline results

The results from the linear panel fixed effects (FE) regressions of crop insurance losses as a function of landscape compositional complexity (e.g., SDI) are presented in Table 2. For the LCR regressions, the parameter estimates for the SDI variable suggest that counties with higher landscape compositional complexity, as indicated by a higher SDI, have statistically lower LCRs due to drought and excess heat (at the 1% significance level). However, no statistically significant relationship is observed between landscape compositional complexity and the LCR associated with excess moisture. For the LAR regressions, the estimated parameters indicate that counties with higher landscape compositional complexity have statistically lower LARs due to drought and excess moisture (at the 5% level of significance). There is no statistically significant relationship between landscape compositional complexity and excess heat-related LAR.

On the other hand, Table 3 shows the parameter estimates for the MPA regressions, which suggest that counties with higher landscape configurational complexity, as indicated by a lower MPA, have statistically significantly lower LCRs and LARs due to excess heat (at the 1% significance level). However, the relationships between landscape configurational complexity and LCRs (or LARs) for drought or excess moisture are either significantly negative or not statistically significant. Overall, empirical results from both Tables 2 and 3 indicate that counties with higher compositional and configurational complexity more consistently mitigate losses due to droughts and excess heat (i.e., the evidence is not as strong and consistent for the landscape complexity effects on excess moisture).

Our findings in Table 2 first suggest that increasing compositional landscape complexity likely has more significant loss mitigation effects against drought by enhancing the resilience

and stability of agricultural systems. Specifically, if a landscape has more compositional diversity, there is a higher likelihood of cultivating multiple crops that can withstand particular weather stressors such as drought, making aggregate productivity across the landscape less volatile to drought.[9] Agricultural intensification has also altered water flows in many agricultural landscapes in ways that exacerbate erosion and soil loss, which in turn can worsen the adverse impacts of drought on crop yields (Gordon et al., 2008). Therefore, greater crop diversity in US counties has been shown to help enhance water retention, water flows, and soil health, such that it reduces the negative impacts of droughts on agricultural outputs (Renard et al., 2023).[10] This result is explained by both crop diversity and also by the sensitivity of the most abundant crops (in terms of harvested areas) to this extreme (Renard et al., 2023). Yield stability significantly increases when corn and soybeans are integrated into more diverse rotations. In hot and dry years, diversification of corn-soybean rotations and reduced tillage have been shown to increase yields by 7% and 22% for corn and soybean, respectively (Gaudin et al., 2015). Moreover, biodiversity has been shown to increase ecosystem resistance to a broad range of climate events, including dry, extreme, and brief or prolonged heat events. Across several studies, the productivity of low-diversity communities (with one or two species) changed by approximately 50% during climate events, whereas high-diversity communities (with 16–32 species) were more resistant, changing by only about 25% (Isbell et al., 2015). Part of this is due to a "composition

[9] Moreover, diverse landscapes support higher biodiversity, including beneficial soil microbes, pollinators, and pest predators. These organisms contribute to crop resilience during water stress. For instance, soil microbial communities in diverse systems enhance nutrient cycling and improve water uptake in plants (Mace et al., 2012).
[10] Complex landscapes provide complementary ecosystem functions, including improved water infiltration, greater rooting depth variability, and more efficient water use (Stephens et al., 2021). For example, forests or perennial vegetation in diverse landscapes can buffer drought impacts by maintaining soil moisture and reducing evapotranspiration rates (Foley et al., 2005). This functional diversity ensures that drought-sensitive crops benefit indirectly from the stability provided by other landscape elements. Diversity from the presence of trees and non-crop vegetation also create localized cooling effects (i.e., improved microclimate regulation) and can shield crops from extreme heat.

effect," where the presence of certain more drought-resistant species in more diverse landscapes drives this enhanced resilience.

Our findings also suggest that increasing compositional and configurational landscape complexity can significantly mitigate losses associated with excess heat. For example, Reidsma and Ewert (2008) show that greater diversity in farm size and management intensity reduces the vulnerability of regional wheat yields to high temperatures, while regions with mostly homogenous larger farms, experience more pronounced negative effects. In addition, greater crop diversity within countries has been shown to reduce the negative impacts of high temperatures on agricultural outputs (Renard et al., 2023). Diversification also improves yield stability, particularly when integrating corn and soybeans into more diverse rotations under heat events. By increasing the probability of harnessing favorable growing conditions and reducing the risk of crop failure, these strategies help buffer yields during hot years (Gaudin et al., 2015). Lastly, although our empirical evidence on the resilience effects of complexity on excess moisture (or floods) is not as consistent as for drought and excess heat events, there are studies that show that more diverse landscapes can also potentially enhance resilience to flood events by improving soil water flow and lowering peak flood levels (Antolini et al., 2020).[11]

Regarding the weather variables considered as controls in Tables 2 and 3, the estimated county-level effects align closely with expectations. Specifically, we observe a nonlinear effect

[11] While compositional and configurational complexity provide resilience against a range of weather extremes, their benefits are likely stronger for drought and heat stress than for flood events for the following reasons. First, during droughts, landscape complexity improves water retention and redistributes limited water resources, buffering crops from the impacts of water scarcity. In contrast, floods often overwhelm local retention capacity and saturate soils regardless of landscape composition, leaving less room for ecological buffering. Second, landscape heterogeneity effectively reduces local temperatures, a critical factor in drought resilience. However, temperature moderation has limited relevance during floods, where excess water are the primary threats to crops. Lastly, flood resilience often depends on macro-level hydrological infrastructure (e.g., levees and drainage systems) rather than micro-level landscape heterogeneity. In contrast, drought and heat resilience are inherently tied to the local landscape's ability to retain moisture and moderate temperature.

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 2 and 3, 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 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.

5.2 Robustness check results: Alternative specifications

As previously mentioned, we evaluate the robustness and stability of our main linear panel FE results by performing several robustness checks with alternative empirical specifications. First, we include both landscape complexity indexes (SDI and MPA) together in a single model for each of our insurance loss variables (Table S1) to account for potential omitted variable bias resulting from their possible correlation. By doing so, we ensure that each index's effect on insurance losses is examined while controlling for the other. The parameter estimates for SDI and MPA remain largely consistent with those obtained in the separate models, except that higher SDI lowers the LCR due to moisture at the 10% significance level, indicating that controlling for both concurrently does not greatly change their individual impacts on crop insurance outcomes. This consistency suggests that SDI and MPA capture somewhat distinct aspects of landscape complexity that jointly affect climate resilience, indicating the robustness of our baseline findings.

Second, we incorporate state-specific trends to account for differential trend responses across states (Table S2). The primary conclusions from these analyses remain consistent with our main linear panel FE results in Table 2. The signs, magnitudes, and statistical significance of the SDI parameter estimates are very similar to those in the main model, with the exception that no significant relationship is found between landscape complexity and LAR due to excess moisture. Third, we include a measure of irrigation use at the county level as an additional control, as irrigation can influence extreme-weather-related losses. The results of this robustness check are presented in Table S3. The LCR and LAR results in Table S3 remain consistent with those from the linear panel FE model with state-specific trends. Fourth, we extend the analysis to only include counties east of the 100th meridian, where farming is predominantly non-irrigated, as irrigation generally does not play a significant role in influencing losses in this region. The results in Table S4 are consistent with those when we include the irrigation use variable and still indicate that increased landscape complexity can help mitigate extreme-weather-related losses, especially due to drought and excess heat. Fifth, instead of using a general time trend variable, we incorporate year-fixed effects into our baseline model, the irrigation use model, and the model focusing on counties east of the 100th meridian. The results are consistent and presented in Tables S5-S7.

In addition, we include the shares of three major crops (corn, soybeans, and wheat) among total planted acres as additional control variables (Table S8) to capture any influence from shifts in crop choices on crop insurance outcomes. Including this measure helps us determine whether the observed effects of landscape diversity (SDI) might be confounded by strategic crop adaptations (e.g., planting more drought-resistant or high-value crops). However, the results show that the share of major crops does not significantly affect most insurance loss variables,

while SDI retains a consistent sign and magnitude as in our baseline model. This finding implies that the relationship between landscape complexity and insurance losses is not merely a reflection of farmers' decisions to concentrate on particular major crops; instead, SDI appears to have an independent effect on resilience outcomes beyond what can be explained by shifts in crop composition. We also estimate how landscape complexity affects crop insurance losses for selected major crops. The results for corn, soybeans, and wheat are presented in Tables S9-S11, respectively, and they are largely consistent with our baseline models.

Finally, we conduct all the above mentioned robustness checks for the other landscape complexity indicator (i.e., MPA) to capture landscape configurational complexity, enabling a further investigation of the impacts of spatial dimensions of landscape complexity on crop insurance losses. Recall that higher MPA values indicate lower configurational complexity. Across the regression tables, our analysis consistently shows that counties with greater configurational complexity (i.e., lower mean patch area) tend to have a lower proportion of loss payments and acres attributed to excess heat. On the other hand, the results for configurational complexity and insurance losses due to drought or excess moisture are less consistent (Tables S12-S21).

5.3 Robustness check results: Alternative estimations

Aside from robustness to alternative specifications, we also evaluate whether our findings generally hold when the main empirical specification is estimated using alternative approaches. First, we use a fractional regression procedure (also called CRE probit) to estimate our main empirical model. This estimation method explicitly accounts for the fractional nature of the LCR and LAR dependent variable while still allowing one to control for unobserved heterogeneity (i.e., time-invariant unobservables). Results for the CRE probit runs for SDI are reported in

Table 4. The estimates from this robustness check still largely coincide with our results from the baseline linear panel FE regressions that increased landscape complexity helps lower crop insurance losses due to droughts, excess heat, or excess moisture. We also get consistent results using the CRE probit model when we consider the other landscape complexity indicator (i.e., MPA) (Table S22).

We also apply the Lewbel (2012) moment-based IV procedure as an additional robustness check to assess whether the results from the linear panel FE model hold when accounting for residual time- and county-varying unobservables. The parameter estimates from this IV procedure for SDI are presented in Table 5. Overall, the results from the moment-based IV model are consistent with those of the main linear panel FE model. The estimates continue to show that counties with higher landscape compositional complexity tend to experience significantly lower crop insurance losses due to drought, excess heat, and excess moisture. Additionally, the moment-based IV results for mean patch area also indicate that increased landscape configurational complexity is associated with reduced crop insurance losses from drought and excess heat (Table S23). Therefore, these findings further support the general conclusion that greater landscape complexity enhances resilience to extreme weather events.

Finally, we employ the KLS regression method as an additional robustness check. This external-instrument-free estimation technique offers an alternative to Lewbel's (2012) moment-based IV approach. We implement KLS at 0.1 increments from 0.1 onward and find that under positive endogeneity levels (e.g., 0.1, 0.2, …, 0.9), when considering compositional complexity,[12] the signs and significance of the SDI parameters remain consistent with our

[12] We implement KLS at -0.1 increments from -0.1 onward and find that under negative endogeneity levels (e.g., -0.1, -0.2, …, -0.9) when considering configurational complexity (mean patch area). The corresponding results are presented in Tables S30-S38. Also, note that the KLS procedures we implement here are on models without county FEs, which allow us to better assess whether results are robust to different assumed levels of endogeneity due to any

baseline linear panel FE results (see Tables S24-S32). In other words, our linear panel FE findings hold firm even when modest levels of endogeneity are assumed. It would take substantially higher endogeneity levels to overturn the baseline results. These KLS results reinforce the notion that our baseline model estimates are robust and likely can withstand modest residual endogeneity from unobservables in the error term.

4. 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 spanning 2008 to 2018 by merging a novel dataset on landscape complexity with publicly available crop insurance loss and weather data. Empirical analysis is conducted using linear panel fixed-effects models and various robustness checks in the empirical analysis. The findings of our empirical analysis suggest that counties with greater landscape complexity tend to have lower crop insurance losses due to drought, excess heat, or excess moisture, but with more consistent evidence of resilience effects against drought and excess heat events. These results underscore the potential of landscape complexity as a factor contributing to the mitigation of weather-related crop insurance losses and improving the resilience of economic returns in US agriculture.

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

type of unobservable (i.e., time-invariant and time-county-varying unobservables). Since our results remain robust at fairly high levels of endogeneity of any kind (i.e., even at 0.6, 0.7, and 0.8), we believe that our main results are fairly strong and are not easily overturned even in the presence of small to moderate levels of endogeneity.

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 there are several study limitations and areas that warrant future investigation. First, our current analysis focuses on one main index for each of the two features of landscape complexity, namely compositional complexity and configurational complexity. To gain a more comprehensive understanding, future studies may examine the impact of landscape complexity on insurance losses by incorporating alternative indicators of landscape complexity (Nelson and Burchfield, 2021). Second, this paper specifically concentrates on crop insurance 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 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 for the future.

References

Abson, D. J., Fraser, E. D. and Benton, T. G. (2013). Landscape diversity and the resilience of agricultural returns: A portfolio analysis of land-use patterns and economic returns from lowland agriculture. *Agriculture & Food Security* 2(2): 1–15.

Aglasan, S., Goodwin, B. K. and Rejesus, R. M. (2023). Risk effects of GM corn: Evidence from crop insurance outcomes and high-dimensional methods. *Agricultural Economics* 54(1): 110–126.

Aglasan, S., Rejesus, R. M., Hagen, S. and Salas, W. (2024). Cover crops, crop insurance losses, and resilience to extreme weather events. *American Journal of Agricultural Economics* 106(4): 1410–1434.

Aguilar, J., Gramig, G. G., Hendrickson, J. R., Archer, D. W., Forcella, F. and Liebig, M. A. (2015). Crop species diversity changes in the United States: 1978–2012. *PLOS ONE* 10: e0136580.

Altieri, M. A. (1999). The ecological role of biodiversity in agroecosystems. *Agriculture, Ecosystems & Environment* 74(1): 19–31.

Altieri, M. A., Funes-Monzote, F. R. and Petersen, P. (2011). Agroecologically efficient agricultural systems for smallholder farmers: Contributions to food sovereignty. *Agronomy and Sustainable Development* 32(1): 1–13.

Annan, F. and Schlenker, W. (2015). Federal crop insurance and the disincentive to adapt to extreme heat. *American Economic Review* 105: 262–266.

Antolini, F., Tate, E., Dalzell, B., Young, N., Johnson, K. and Hawthorne, P. L. (2020). Flood risk reduction from agricultural best management practices. *Journal of the American Water Resources Association* 56(1): 161–179.

Bastian, O., Grunewald, K., Syrbe, R.U., Walz, U. and Wende, W. (2014). Landscape services: The concept and its practical relevance. *Landscape Ecology* 29(9): 1463–1479.

Bateni, F., Fakheran, S. and Soffianian, A. (2013). Assessment of land cover changes & water quality changes in the Zayandehroud River Basin between 1997–2008. *Environmental Monitoring and Assessment* 185: 10511–10519.

Baum, C. F. and Lewbel, A. (2019). Advice on using heteroskedasticity-based identification. *The Stata Journal* 19(4): 757–767.

Borin, M., Passoni, M., Thiene, M. and Tempesta, T. (2010). Multiple functions of buffer strips in farming areas. *European Journal of Agronomy* 32: 103–111.

Breusch, T. S. and Pagan, A. R. (1979). A simple test for heteroscedasticity and random coefficient variation. *Econometrica* 47: 1287–1294.

Burchfield, E. K., Nelson, K. S. and Spangler, K. (2019). The impact of agricultural landscape diversification on US crop production. *Agriculture, Ecosystems & Environment* 285: 106615.

Cameron, A. C., Gelbach, J. B. and Miller, D. L. (2011). Robust inference with multiway clustering. *Journal of Business & Economic Statistics* 29: 238–249.

Christman, M. E., Spears, L. R., Burchfield, E. K., Pearse, W. D., Strange, J. P. and Ramirez, R. A. (2024). Bumble bee responses to climate and landscapes: Investigating habitat associations and species assemblages across geographic regions in the United States of America. *Global Change Biology* 30(6): e17380.

Cook, B. I., Ault, T. R. and Smerdon, J. E. (2015). Unprecedented 21st century drought risk in the American Southwest and Central Plains. *Science Advances* 1: e1400082.

D'Agostino, A. L. and Schlenker, W. (2016). Recent weather fluctuations and agricultural yields: Implications for climate change. *Agricultural Economics* 47: 159–171.

Dalzell, B. J. and Mulla, D. J. (2018). Perennial vegetation impacts on stream discharge and channel sources of sediment in the Minnesota River Basin. *Journal of Soil and Water Conservation* 73(2): 120–132.

Duarte, G. T., Santos, P. M., Cornelissen, T. G., Ribeiro, M. C. and Paglia, A. P. (2018). The effects of landscape patterns on ecosystem services: Meta-analyses of landscape services. *Landscape Ecology* 33: 1247–1257.

Fabri, C., Vermeulen, S., Van Passel, S. and Schaub, S. (2024). Crop diversification and the effect of weather shocks on Italian farmers' income and income risk. *Journal of Agricultural Economics* 75(3): 955–980.

Fahrig, L., Baudry, J., Brotons, L., Burel, F. G., Crist, T. O., Fuller, R. J., Sirami, C., Siriwardena, G. M. and Martin, J. L. (2011). Functional landscape heterogeneity and animal biodiversity in agricultural landscapes. *Ecology Letters* 14: 101–112.

Foley, J.A., DeFries, R., Asner, G.P., Barford, C., Bonan, G., Carpenter, S.R., Chapin, F.S., Coe, M.T., Daily, G.C., Gibbs, H.K. and Helkowski, J.H. (2005). Global consequences of land use. *Science* 309(5734): 570–574.

Gardiner, M.M., Landis, D.A., Gratton, C., DiFonzo, C.D., O'neal, M., Chacon, J.M., Wayo, M.T., Schmidt, N.P., Mueller, E.E. and Heimpel, G.E. (2009). Landscape diversity enhances biological control of an introduced crop pest in the North-Central USA. *Ecological Applications* 19(1): 143–154.

Gaudin, A.C., Tolhurst, T.N., Ker, A.P., Janovicek, K., Tortora, C., Martin, R.C. and Deen, W. (2015). Increasing crop diversity mitigates weather variations and improves yield stability. *PLOS ONE* 10(2): e0113261.

Gordon, L. J., Peterson, G. D. and Bennett, E. M. (2008). Agricultural modifications of hydrological flows create ecological surprises. *Trends in Ecology & Evolution* 23(4): 211–219.

Grab, H., Branstetter, M.G., Amon, N., Urban-Mead, K.R., Park, M.G., Gibbs, J., Blitzer, E.J., Poveda, K., Loeb, G. and Danforth, B.N. (2019). Agriculturally dominated landscapes reduce bee phylogenetic diversity and pollination services. *Science* 363(6424): 282–284.

Hatt, S., Boeraeve, F., Artru, S., Dufrêne, M. and Francis, F. (2018). Spatial diversification of agroecosystems to enhance biological control and other regulating services: An agroecological perspective. *Science of The Total Environment* 621: 600–611.

Isbell, F., Craven, D., Connolly, J., Loreau, M., Schmid, B., Beierkuhnlein, C., Bezemer, T.M., Bonin, C., Bruelheide, H., De Luca, E. and Ebeling, A. (2015). Biodiversity increases the

resistance of ecosystem productivity to climate extremes. *Nature* 526: 574–579.

Kelly, S. A., Takbiri, Z., Belmont, P. and Foufoula-Georgiou, E. (2017). Human amplified changes in precipitation–runoff patterns in large river basins of the Midwestern United States. *Hydrology and Earth System Sciences* 21(10): 5065–5088.

Kiviet, J. F. (2013). Identification and inference in a simultaneous equation under alternative information sets and sampling schemes. *Econometrics Journal* 16:S24–S59.

Kiviet, J. F. (2020). Testing the impossible: Identifying exclusion restrictions. *Journal of Econometrics* 218: 294–316.

Kleibergen, F. and Paap, R. (2006). Generalized reduced rank tests using the singular value decomposition. *Journal of Econometrics* 133: 97–126.

Klein, A. M., Müller, C., Hoehn, P. and Kremen, C. (2009). Understanding the role of species richness for crop pollination services. *Biodiversity, Ecosystem Function and Human Wellbeing. New York,* 195–208.

Kripfganz, S. and Kiviet, J. F. (2021). Kinkyreg: Instrument-free inference for linear regression models with endogenous regressors. *Stata Journal* 21: 772–813.

Landis, D. A. (2017). Designing agricultural landscapes for biodiversity-based ecosystem services. *Basic and Applied Ecology* 18: 1–12.

Lenka, N. K., Dass, A., Sudhishri, S. and Patnaik, U. S. (2012). Soil carbon sequestration and erosion control potential of hedgerows and grass filter strips in sloping agricultural lands of Eastern India. *Agriculture, Ecosystems & Environment* 158: 31–40.

Lewbel, A. (2012). Using heteroscedasticity to identify and estimate mismeasured and endogenous regressor models. *Journal of Business & Economic Statistics* 30: 67–80.

Liu, W., Zhang, Q. and Liu, G. (2012). Influences of watershed landscape composition and configuration on lake-water quality in the Yangtze River Basin of China. *Hydrological Processes* 26(4): 570–578.

Mace, G. M., Norris, K. and Fitter, A. H. (2012). Biodiversity and ecosystem services: A multilayered relationship. *Trends in Ecology & Evolution* 27(1): 19–26.

Marshall, M.R., Francis, O.J., Frogbrook, Z.L., Jackson, B.M., McIntyre, N., Reynolds, B., Solloway, I., Wheater, H.S. and Chell, J. (2009). The impact of upland land management on flooding: Results from an improved pasture hillslope. *Hydrological Processes* 23(3): 464–475.

Mayor, Á. G., Bautista, S. and Bellot, J. (2011). Scale-dependent variation in runoff and sediment yield in a semiarid Mediterranean catchment. *Journal of Hydrology* 397(1): 128–135.

McDaniel, M. D., Tiemann, L. K. and Grandy, A. S. (2014). Does agricultural crop diversity enhance soil microbial biomass and organic matter dynamics? A meta-analysis. *Ecological Applications* 24(3): 560–570.

Meehan, T. D., Werling, B. P., Landis, D. A. and Gratton, C. (2011). Agricultural landscape simplification and insecticide use in the Midwestern United States. *Proceedings of the National Academy of Sciences* 108: 11500–11505.

Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econometrica* 46: 69–85.

Nelson, K. S. and Burchfield, E. K. (2021). Landscape complexity and US crop production. *Nature Food* 2: 330–338.

Nicholson, C. C., Koh, I., Richardson, L. L., Beauchemin, A. and Ricketts, T. H. (2017). Farm and landscape factors interact to affect the supply of pollination services. *Agriculture, Ecosystems & Environment* 250: 113–122.

Nottebrock, H., Burchfield, E. K. and Fenster, C. B. (2022). Farmers' delivery of floral resources: To 'bee' or not to 'bee'. *American Journal of Botany* 109(1): 4–8.

Perry, E. D., Yu, J. and Tack, J. (2020). Using insurance data to quantify the multidimensional impacts of warming temperatures on yield risk. *Nature Communications* 11: 4542.

Plexida, S. G., Sfougaris, A. I., Ispikoudis, I. P. and Papanastasis, V. P. (2014). Selecting landscape metrics as indicators of spatial heterogeneity—A comparison among Greek landscapes. *International Journal of Applied Earth Observation and Geoinformation* 26: 26–35.

Post, W. M. and Kwon, K. C. (2000). Soil carbon sequestration and land use change: Processes and potential. *Global Change Biology* 6: 317–327.

Prokopy, L.S., Gramig, B.M., Bower, A., Church, S.P., Ellison, B., Gassman, P.W., Genskow, K., Gucker, D., Hallett, S.G., Hill, J. and Hunt, N. (2020). The urgency of transforming the Midwestern US landscape into more than corn and soybean. *Agriculture and Human Values* 37: 537–539.

Reidsma, P. and Ewert, F. (2008). Regional farm diversity can reduce vulnerability of food production to climate change. *Ecology and Society* 13(1): 38.

Renard, D., Mahaut, L. and Noack, F. (2023). Crop diversity buffers the impact of droughts and high temperatures on food production. *Environmental Research Letters* 18(4): 045005.

Ricketts, T.H., Regetz, J., Steffan-Dewenter, I., Cunningham, S.A., Kremen, C., Bogdanski, A., Gemmill-Herren, B., Greenleaf, S.S., Klein, A.M., Mayfield, M.M. and Morandin, L.A. (2008). Landscape effects on crop pollination services: Are there general patterns? *Ecology Letters* 11(5): 499–515.

Rusch, A., Chaplin-Kramer, R., Gardiner, M.M., Hawro, V., Holland, J., Landis, D., Thies, C., Tscharntke, T., Weisser, W.W., Winqvist, C. and Woltz, M. (2016). Agricultural landscape simplification reduces natural pest control: A quantitative synthesis. *Agriculture, Ecosystems & Environment* 221: 198–204.

Schilling, K.E., Gassman, P.W., Kling, C.L., Campbell, T., Jha, M.K., Wolter, C.F. and Arnold, J.G. (2014). The potential for agricultural land use change to reduce flood risk in a large watershed. *Hydrological Processes* 28(8): 3314–3325.

Schindler, S., Poirazidis, K. and Wrbka, T. (2008). Towards a core set of landscape metrics for biodiversity assessments: A case study from Dadia National Park, Greece. *Ecological Indicators* 8: 502–514.

Schlenker, W. and Roberts, M. J. (2006). Nonlinear effects of weather on corn yields. *Review of*

Agricultural Economics 28: 391–398.

Schlenker, W. and Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proceedings of the National Academy of Sciences* 106: 15594–15598.

Schulte, L.A., Niemi, J., Helmers, M.J., Liebman, M., Arbuckle, J.G., James, D.E., Kolka, R.K., O'Neal, M.E., Tomer, M.D., Tyndall, J.C. and Asbjornsen, H. (2017). Prairie strips improve biodiversity and the delivery of multiple ecosystem services from corn–soybean croplands. *Proceedings of the National Academy of Sciences* 114(42): 11247–11252.

Shi, Z.H., Ai, L., Li, X., Huang, X.D., Wu, G.L. and Liao, W. (2013). Partial least-squares regression for linking land-cover patterns to soil erosion and sediment yield in watersheds. *Journal of Hydrology* 498: 165–176.

Skees, J. R., Barnett, B. J. and Collier, B. (2008). Agricultural insurance: Background and context for climate adaptation discussions. In *Prepared for the OECD Expert Workshop on Economic Aspects of Adaptation.*

Sriwongsitanon, N. and Taesombat, W. (2011). Effects of land cover on runoff coefficient. *Journal of Hydrology* 410(3): 226–238.

Stephens, C. M., Lall, U., Johnson, F. M. and Marshall, L. A. (2021). Landscape changes and their hydrologic effects: Interactions and feedbacks across scales. *Earth-Science Reviews* 212: 103466.

Stocker, T. (2014). *Climate Change 2013: The Physical Science Basis: Working Group I contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press.

Sun, R., Chen, L., Chen, W. and Ji, Y. (2013). Effect of land-use patterns on total nitrogen concentration in the upstream regions of the Haihe River Basin, China. *Environmental Management* 51(1): 45–58.

Tack, J., Barkley, A. and Nalley, L. L. (2015). Effect of warming temperatures on US wheat yields. *Proceedings of the National Academy of Sciences* 112: 6931–6936.

Termorshuizen, J. W. and Opdam, P. (2009). Landscape services as a bridge between landscape ecology and sustainable development. *Landscape Ecology* 24(8): 1037–1052.

Tiemann, L. K., Grandy, A. S., Atkinson, E. E., Marin-Spiotta, E. and McDaniel, M. D. (2015). Crop rotational diversity enhances belowground communities and functions in an agroecosystem. *Ecology Letters* 18(8): 761–771.

Turner, M. G. (1990). Spatial and temporal analysis of landscape patterns. *Landscape Ecology* 4: 21–30.

Vasiliev, D. and Greenwood, S. (2020). Pollinator biodiversity and crop pollination in temperate ecosystems, implications for national pollinator conservation strategies: A mini review. *Science of the Total Environment* 744: 140880.

Veres, A., Petit, S., Conord, C. and Lavigne, C. (2013). Does landscape composition affect pest abundance and their control by natural enemies? A review. *Agriculture, Ecosystems & Environment* 166: 110–117.

Verhagen, W., Van Teeffelen, A.J., Baggio Compagnucci, A., Poggio, L., Gimona, A. and Verburg, P.H. (2016). Effects of landscape configuration on mapping ecosystem service capacity: A review of evidence and a case study in Scotland. *Landscape Ecology* 31(7): 1457–1479.

Von Freyberg, J., Radny, D., Gall, H. E. and Schirmer, M. (2014). Implications of hydrologic connectivity between hillslopes and riparian zones on streamflow composition. *Journal of Contaminant Hydrology* 169: 62–74.

Wang, R., Rejesus, R. M., Tack, J. B. and Aglasan, S. (2021). Do higher temperatures influence how yields respond to increasing planting density? *Agricultural and Resource Economics Review* 50: 273–295.

Won, S., Rejesus, R. M., Goodwin, B. K. and Aglasan, S. (2024). Understanding the effect of cover crop use on prevented planting losses. *American Journal of Agricultural Economics* 106(2): 659–683.

Wooldridge, J. M. (2019). Correlated random effects models with unbalanced panels. *Journal of Econometrics* 211: 137–150.

Wuest, S. (2014). Seasonal variation in soil organic carbon. *Soil Science Society of America Journal* 78: 1442–1447.

Xu, Z., Hennessy, D. A., Sardana, K. and Moschini, G. (2013). The realized yield effect of genetically engineered crops: US maize and soybean. *Crop Science* 53: 735–745.

Yang, L., Liu, B., Zhang, Q., Zeng, Y., Pan, Y., Li, M. and Lu, Y. (2019). Landscape structure alters the abundance and species composition of early-season aphid populations in wheat fields. *Agriculture, Ecosystems & Environment* 269: 167–173.

Yang, M., Li, X., Hu, Y. and He, X. (2012). Assessing effects of landscape pattern on sediment yield using sediment delivery distributed model and a landscape indicator. *Ecological Indicators* 22: 38–52.

Figures and Tables

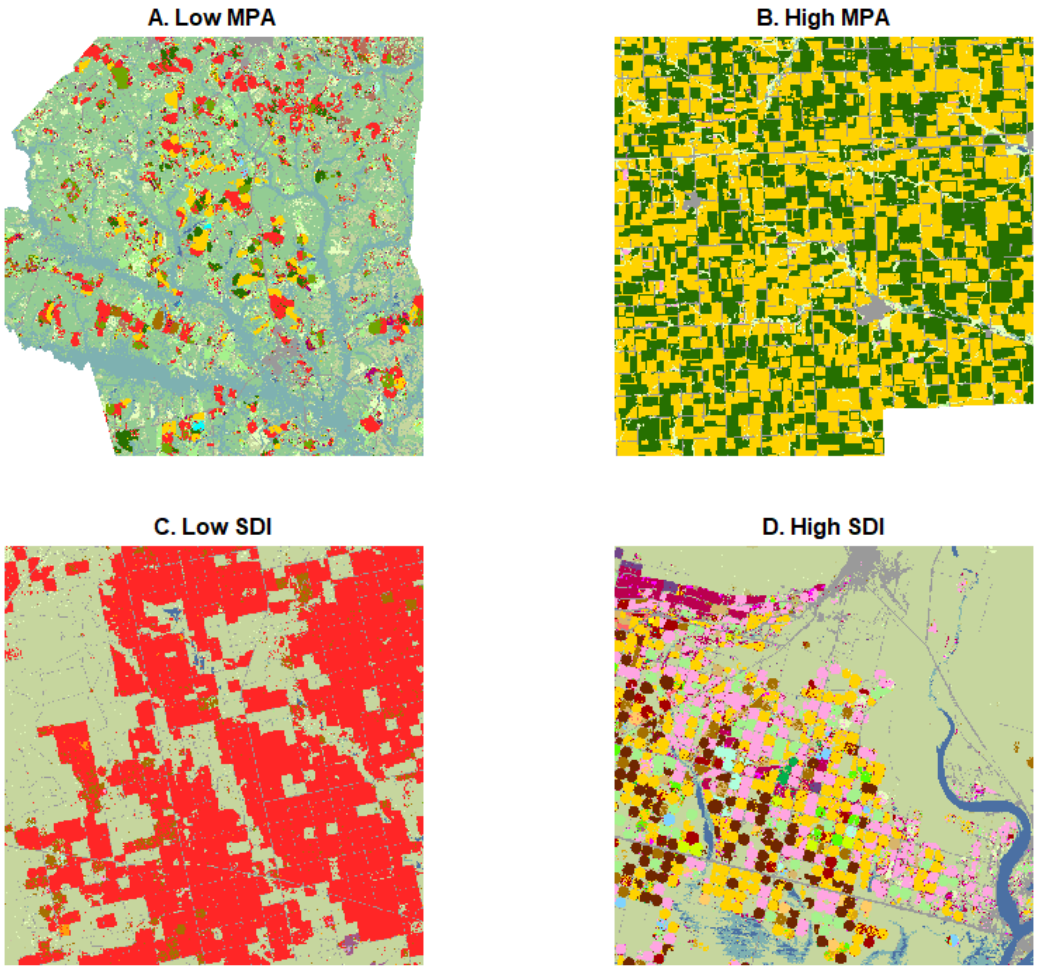
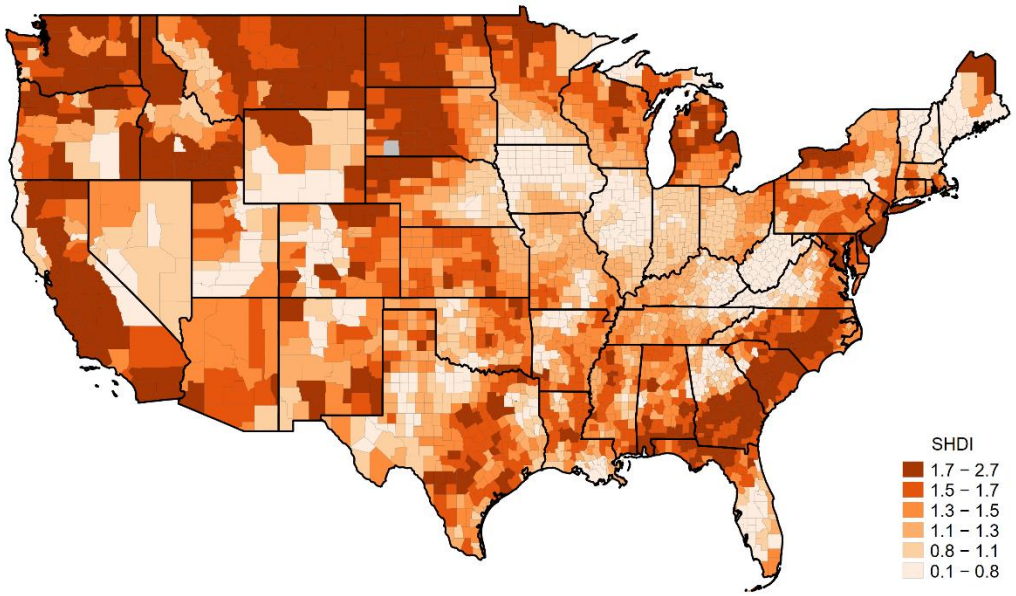
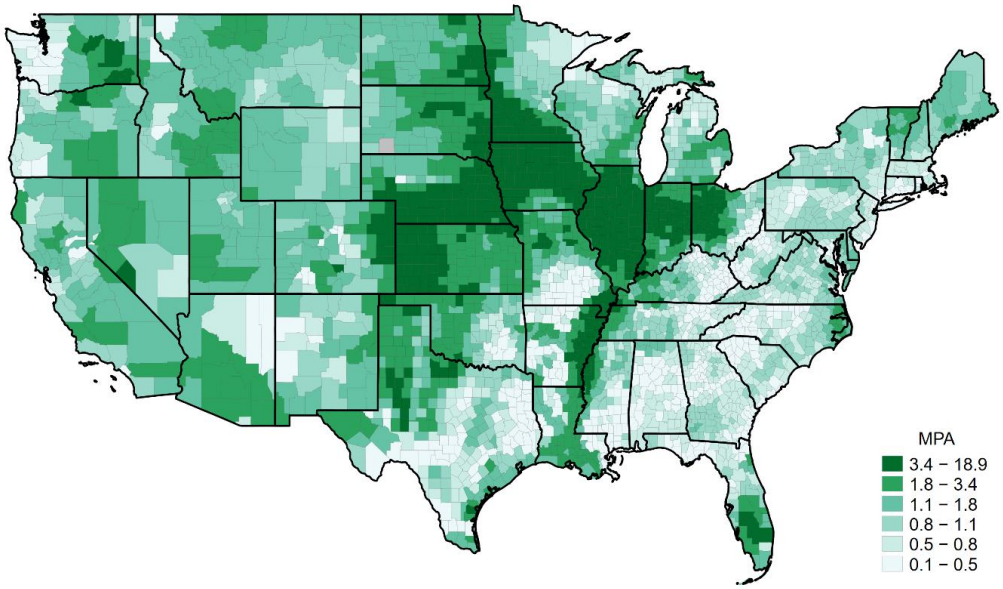


Figure 1. 1000 x 1000 pixel visualizations of US counties with (A) low Mean Patch Area (MPA) (Jefferson County, GA), (B) high Mean Patch Area (Grundy County, Iowa), (C) low Shannon Diversity Index (SDI) (Martin County, Texas) and (D) high Shannon Diversity index (Grant County, Washington)



(a) Landscape compositional complexity: Shannon Diversity Index (SDI)



(b) Landscape configurational complexity: Mean Patch Area (MPA)

Figure 2. Spatial variation in landscape complexity across counties in the United States. Values presented are the average across all years (2008-2018) for Shannon Diversity Index (SDI) and Mean Patch Area (MPA)

Table 1. 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	Landscape compositional complexity index	29,486	1.71	0.42	0.04	3.03
Mean Patch Area	Landscape configurational complexity index	28,878	2.27	2.59	0.13	31.51
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 2. The effect of landscape compositional complexity (Shannon Diversity Index) on weather-related crop insurance losses: Linear fixed effects model

	LCR			LAR		
Variable	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Shannon Diversity Index	-1.272***	-0.300***	0.085	-1.215**	-0.011	-0.857**
	(0.358)	(0.089)	(0.246)	(0.533)	(0.145)	(0.403)
HDD	0.091***	0.015***	0.001	0.087***	0.021***	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)
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29486	29464	29464	29486	29458	29486
Adjusted R^2	0.280	0.101	0.099	0.252	0.092	0.118

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

Table 3. The effect of landscape configurational complexity (Mean Patch Area) on weather-related crop insurance losses: Linear fixed effects model

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Mean Patch Area	0.074	0.046***	-0.468***	-0.195*	0.070***	-1.058***
	(0.071)	(0.010)	(0.108)	(0.117)	(0.018)	(0.100)
HDD	0.091***	0.015***	0.000	0.086**	0.020***	0.006***
	(0.004)	(0.001)	(0.001)	(0.005)	(0.002)	(0.002)
GDD	-0.003***	0.001***	-0.000	0.007***	0.001***	-0.003***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Precipitation	-0.043***	-0.001***	0.008***	-0.064***	-0.001	0.016***
	(0.002)	(0.000)	(0.001)	(0.003)	(0.001)	(0.002)
Precipitation sq.	0.000***	0.000*	0.000	0.000***	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
County-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28878	28857	28857	28878	28851	28878
Adjusted R^2	0.282	0.101	0.104	0.256	0.095	0.126

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

Table 4. The effect of landscape compositional complexity (Shannon Diversity Index) on weather-related crop insurance losses:

Correlated random effects (CRE) model

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Shannon Diversity Index	-0.628*	-0.150**	0.058	-0.398	0.142	-0.832*
	(0.321)	(0.075)	(0.255)	(0.499)	(0.140)	(0.425)
HDD	0.029***	0.006***	-0.003**	0.042**	0.012***	-0.004
	(0.002)	(0.001)	(0.001)	(0.004)	(0.001)	(0.003)
GDD	0.004***	0.001**	-0.001**	0.009***	0.002***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Precipitation	-0.012**	0.000	0.020***	-0.027***	0.001**	0.040***
	(0.002)	(0.000)	(0.001)	(0.003)	(0.001)	(0.002)
Precipitation sq.	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
County-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29486	29464	29464	29486	29458	29486

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

Table 5. The effect of landscape compositional complexity (Shannon Diversity Index) on weather-related crop insurance losses:

Moment-based IV model

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Shannon Diversity Index	-2.122*	-0.879***	-4.573***	-0.881	-0.112	-8.575***
	(1.171)	(0.283)	(0.704)	(1.859)	(0.380)	(1.166)
HDD	0.090***	0.014***	-0.001	0.087***	0.020***	0.005**
	(0.004)	(0.001)	(0.001)	(0.005)	(0.002)	(0.002)
GDD	-0.004***	0.001**	-0.001***	0.007***	0.001***	-0.004***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Precipitation	-0.043***	-0.001***	0.009***	-0.062***	-0.001	0.018***
	(0.002)	(0.000)	(0.001)	(0.003)	(0.001)	(0.002)
Precipitation sq.	0.000***	0.000**	0.000	0.000***	-0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
State-specific trend	Yes	Yes	Yes	Yes	Yes	Yes
County-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29486	29464	29464	29486	29458	29486
Adjusted R^2	0.211	0.010	-0.004	0.191	0.008	0.027
AIC	196452.198	112035.605	168450.472	222399.378	135091.838	206170.335
BIC	196891.657	112475.024	168889.891	222838.837	135531.246	206609.794
Kleibergen-Paap rk LM statistic	534.938	535.684	535.684	535.041	535.137	534.954
	($p = 0.000$)	($p = 0.000$)	($p = 0.000$)	($p = 0.000$)	($p = 0.000$)	($p = 0.000$)
Kleibergen-Paap rk Wald F statistic	57.923	58.190	58.190	57.984	58.152	58.029
(Stock-Yogo 20% max)	48.45	48.45	48.45	48.45	48.45	48.45
Hansen J statistic	220.564	133.532	190.764	235.731	110.143	220.661
	($p = 0.000$)	($p = 0.000$)	($p = 0.000$)	($p = 0.000$)	($p = 0.000$)	($p = 0.000$)

Notes: (i) *** p < 0.01, ** p < 0.05, * p < 0.1. (ii) Standard errors are in parentheses. (iii) The Kliebergen-Paap rk LM stat, Kliebergen-Paap rk Wald stat, and Hansen J stat are diagnostic tests that aim to help assess the appropriateness of the IVs used and the estimation procedure.

Supplemental Materials for

"Landscape Complexity Mitigates Weather-Related Crop Insurance Losses and Enhances Climate Resilience"

Table S1. The effect of landscape compositional and configurational complexity on weather-related crop insurance losses: Linear fixed effects model

	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
SDI	-1.158***	-0.243***	-0.470*	-1.352**	0.086	-2.183***
	(0.376)	(0.091)	(0.256)	(0.550)	(0.150)	(0.432)
MPA	0.016	0.033***	-0.492***	-0.263**	0.075***	-1.168***
	(0.074)	(0.010)	(0.051)	(0.122)	(0.018)	(0.110)
HDD	0.090***	0.015***	0.000	0.086***	0.021***	0.006**
	(0.004)	(0.001)	(0.001)	(0.005)	(0.002)	(0.002)
GDD	-0.003***	0.001***	-0.001***	0.007***	0.001***	-0.004***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Precipitation	-0.043***	-0.001***	0.008***	-0.064***	-0.001	0.016***
	(0.002)	(0.000)	(0.001)	(0.003)	(0.001)	(0.002)
Precipitation sq.	0.000***	0.000**	0.000*	0.000***	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28878	28857	28857	28878	28851	28878
Adjusted R^2	0.283	0.101	0.104	0.256	0.095	0.127

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

Table S2. The effect of landscape compositional complexity (Shannon Diversity Index) on weather-related crop insurance losses: Linear fixed effects model with state-specific trend

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Shannon Diversity Index	-1.226***	-0.333***	0.327	-1.523***	-0.068	-0.194
	(0.381)	(0.089)	(0.246)	(0.542)	(0.148)	(0.403)
HDD	0.090***	0.014***	0.000	0.087***	0.020***	0.007***
	(0.004)	(0.001)	(0.001)	(0.005)	(0.002)	(0.002)
GDD	-0.003***	0.001***	-0.000	0.007***	0.001***	-0.002***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Precipitation	-0.043***	-0.001***	0.009***	-0.062***	-0.001	0.018***
	(0.002)	(0.000)	(0.001)	(0.003)	(0.001)	(0.002)
Precipitation sq.	0.000***	0.000**	0.000	0.000***	-0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
State-specific trend	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29486	29464	29464	29486	29458	29486
Adjusted R^2	0.287	0.108	0.118	0.269	0.103	0.140

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

Table S3. The effect of landscape compositional complexity (Shannon Diversity Index) on weather-related crop insurance losses: Linear fixed effects model with state-specific trends and irrigation variable

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Shannon Diversity Index	-1.231***	-0.333***	0.326	-1.529***	-0.068	-0.198
	(0.381)	(0.089)	(0.246)	(0.542)	(0.148)	(0.403)
HDD	0.090***	0.014***	0.000	0.087***	0.020***	0.007***
	(0.004)	(0.001)	(0.001)	(0.005)	(0.002)	(0.002)
GDD	-0.003***	0.001***	-0.000	0.007***	0.001***	-0.002***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Precipitation	-0.043***	-0.001***	0.009***	-0.062***	-0.001	0.018***
	(0.002)	(0.000)	(0.001)	(0.003)	(0.001)	(0.002)
Precipitation sq.	0.000***	0.000**	0.000	0.000***	-0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Irrigation	0.011**	-0.000	0.002	0.010	0.000	0.007
	(0.004)	(0.001)	(0.002)	(0.007)	(0.003)	(0.004)
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
State-specific trend	Yes	Yes	Yes	Yes	Yes	Yes
County-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29486	29464	29464	29486	29458	29486
Adjusted R^2	0.287	0.108	0.118	0.269	0.103	0.140

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

Table S4. The effect of landscape compositional complexity(Shannon Diversity Index) on weather-related crop insurance losses in counties east of the 100th meridian: Linear fixed effects model with state-specific trend

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Shannon Diversity Index	-1.739***	-0.468***	0.501	-2.856***	-0.232	-0.474
	(0.477)	(0.145)	(0.373)	(0.728)	(0.225)	(0.568)
HDD	0.109***	0.019***	0.006***	0.146***	0.031***	-0.000
	(0.005)	(0.002)	(0.001)	(0.007)	(0.002)	(0.003)
GDD	-0.004***	0.001***	-0.000	0.003***	-0.000	-0.002*
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Precipitation	-0.044***	-0.001***	0.009***	-0.079***	-0.001	0.018***
	(0.003)	(0.001)	(0.001)	(0.004)	(0.001)	(0.002)
Precipitation sq.	0.000***	0.000**	0.000	0.000***	-0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
State-specific trend	Yes	Yes	Yes	Yes	Yes	Yes
County-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19327	19327	19327	19327	19327	19327
Adjusted R^2	0.361	0.140	0.153	0.369	0.155	0.189

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

Table S5. The effect of landscape compositional complexity (Shannon Diversity Index) on crop insurance loss: Linear fixed effects models with year fixed and county fixed effects

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Shannon Diversity Index	-1.697***	-0.270***	0.021	-2.062***	-0.018	-0.936**
	(0.371)	(0.090)	(0.246)	(0.555)	(0.146)	(0.401)
HDD	0.105***	0.015***	0.006***	0.102***	0.020***	0.023***
	(0.004)	(0.001)	(0.001)	(0.006)	(0.002)	(0.003)
GDD	0.005***	0.000	-0.002***	0.016***	0.001***	-0.006***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Precipitation	-0.028***	-0.001***	0.005***	-0.042***	-0.000	0.011***
	(0.002)	(0.000)	(0.001)	(0.003)	(0.001)	(0.003)
Precipitation sq.	0.000***	0.000**	0.000***	0.000***	-0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29486	29464	29464	29486	29458	29486
Adjusted R^2	0.306	0.104	0.129	0.285	0.097	0.151

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

Table S6. The effect of landscape compositional complexity (Shannon Diversity Index) on crop insurance loss: Linear fixed effects models with year fixed effects, county fixed effects, and irrigation variable

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Shannon Diversity Index	-1.704***	-0.270***	0.019	-2.072***	-0.018	-0.941**
	(0.371)	(0.090)	(0.246)	(0.555)	(0.146)	(0.402)
HDD	0.105***	0.015***	0.006***	0.102***	0.020***	0.023***
	(0.004)	(0.001)	(0.001)	(0.006)	(0.002)	(0.003)
GDD	0.005***	0.000	-0.002***	0.017***	0.001***	-0.005***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Precipitation	-0.028***	-0.001***	0.005***	-0.042***	-0.000	0.011***
	(0.002)	(0.000)	(0.001)	(0.003)	(0.001)	(0.003)
Precipitation sq.	0.000***	0.000**	0.000***	0.000***	-0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Irrigation	0.021***	0.001	0.007***	0.026***	0.001	0.015***
	(0.005)	(0.001)	(0.002)	(0.008)	(0.003)	(0.005)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29486	29464	29464	29486	29458	29486
Adjusted R^2	0.307	0.104	0.129	0.285	0.097	0.151

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

Table S7. The effect of landscape compositional complexity (Shannon Diversity Index) on crop insurance loss in counties east of the 100th meridian: Linear fixed effects models with year fixed and county fixed effects

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Shannon Diversity Index	-3.178***	-0.460***	0.253	-5.200***	-0.355	-1.348**
	(0.469)	(0.146)	(0.371)	(0.762)	(0.221)	(0.569)
HDD	0.128***	0.020***	0.006***	0.161***	0.030***	0.031***
	(0.005)	(0.002)	(0.002)	(0.007)	(0.002)	(0.004)
GDD	0.015***	-0.001**	-0.003***	0.032***	-0.002***	-0.010***
	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.002)
Precipitation	-0.023***	0.001	0.002	-0.047***	0.001	0.009**
	(0.003)	(0.001)	(0.002)	(0.004)	(0.001)	(0.004)
Precipitation sq.	0.000***	-0.000	0.000***	0.000***	-0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19327	19327	19327	19327	19327	19327
Adjusted R^2	0.401	0.138	0.173	0.408	0.153	0.214

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

Table S8. The effect of landscape compositional complexity (Shannon Diversity Index) on weather-related crop insurance losses: Linear fixed effects model with crop share measures

	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
SDI	-2.755***	-0.740***	0.536	-5.650***	-1.067***	-2.008**
	(0.737)	(0.217)	(0.587)	(1.181)	(0.283)	(0.982)
HDD	0.138***	0.024***	-0.007***	0.221***	0.041***	-0.011**
	(0.008)	(0.002)	(0.002)	(0.012)	(0.002)	(0.005)
GDD	-0.009***	-0.002***	0.001	-0.013***	-0.003***	-0.003**
	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.001)
Precipitation	-0.054***	-0.003***	0.008***	-0.107***	-0.004***	0.017***
	(0.005)	(0.001)	(0.003)	(0.007)	(0.001)	(0.005)
Precipitation sq.	0.000***	0.000**	0.000	0.000***	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Corn share	7.361***	1.421***	0.889	13.110***	1.788***	-2.678
	(2.549)	(0.317)	(1.420)	(4.101)	(0.524)	(2.410)
Soybean share	-3.101*	-0.145	1.690	-4.227	-0.108	6.019**
	(1.874)	(0.225)	(1.686)	(3.213)	(0.376)	(2.562)
Wheat share	0.386	-0.048	0.368	0.333	-0.027	0.262
	(0.384)	(0.030)	(0.249)	(0.680)	(0.050)	(0.362)
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8071	8071	8071	8071	8071	8071
Adjusted R^2	0.440	0.272	0.117	0.464	0.303	0.148

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

Table S9. The effect of landscape compositional complexity (Shannon Diversity Index) on crop insurance loss for corn: Linear fixed effects models

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Shannon Diversity Index	-2.568***	-0.248	-0.692	-3.299***	-0.468	-3.318***
	(0.824)	(0.215)	(0.449)	(0.912)	(0.316)	(0.880)
HDD	0.105***	0.035***	0.007***	0.131***	0.055***	0.028***
	(0.006)	(0.002)	(0.002)	(0.008)	(0.003)	(0.004)
GDD	-0.002	-0.002***	-0.004***	0.002	-0.004***	-0.005***
	(0.001)	(0.000)	(0.001)	(0.002)	(0.001)	(0.001)
Precipitation	-0.038***	-0.005***	0.008***	-0.068***	-0.010***	0.019***
	(0.004)	(0.001)	(0.003)	(0.005)	(0.002)	(0.004)
Precipitation sq.	0.000***	0.000***	0.000*	0.000***	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28061	20025	20025	28061	20025	28061
Adjusted R^2	0.105	0.132	0.099	0.164	0.143	0.041

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

Table S10. The effect of landscape compositional complexity (Shannon Diversity Index) on crop insurance loss for soybeans: Linear fixed effects models

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Shannon Diversity Index	-4.458***	0.205	1.089*	-5.471***	0.069	-2.586***
	(0.831)	(0.257)	(0.591)	(0.875)	(0.355)	(0.897)
HDD	0.075***	0.029***	-0.014***	0.113***	0.053***	0.010**
	(0.005)	(0.003)	(0.003)	(0.007)	(0.004)	(0.004)
GDD	-0.002**	-0.002***	-0.002***	-0.000	-0.003***	-0.005***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Precipitation	-0.007**	-0.005***	0.002	-0.026***	-0.008***	0.013***
	(0.003)	(0.001)	(0.004)	(0.004)	(0.002)	(0.004)
Precipitation sq.	0.000	0.000***	0.000**	0.000*	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28648	17888	17888	28648	17888	28648
Adjusted R^2	0.063	0.073	0.093	0.131	0.106	0.028

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

Table S11. The effect of landscape compositional complexity (Shannon Diversity Index) on crop insurance loss for wheat: Linear fixed effects models

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Shannon Diversity Index	-2.138**	0.271	-7.312***	-2.497***	0.517*	-8.858***
	(0.904)	(0.214)	(0.895)	(0.957)	(0.273)	(1.013)
HDD	0.015***	-0.002***	-0.011***	0.016***	-0.004***	-0.006
	(0.005)	(0.000)	(0.004)	(0.006)	(0.001)	(0.006)
GDD	-0.000	0.001***	0.026***	0.000	0.002***	0.035***
	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.002)
Precipitation	-0.046***	-0.001***	0.031***	-0.074***	-0.002***	0.042***
	(0.005)	(0.000)	(0.004)	(0.006)	(0.001)	(0.004)
Precipitation sq.	0.000***	0.000**	-0.000***	0.000***	0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28653	19680	19680	28653	19680	28653
Adjusted R^2	0.012	0.003	0.067	0.024	0.005	0.041

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

Table S12. The effect of landscape configurational complexity (Mean Patch Area) on weather-related crop insurance losses: Linear fixed effects model with state-specific trend

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Mean Patch Area	0.085	0.046***	-0.503***	-0.218*	0.066***	-1.081***
	(0.072)	(0.010)	(0.050)	(0.118)	(0.017)	(0.100)
HDD	0.090***	0.014***	0.000	0.086**	0.020***	0.006**
	(0.004)	(0.001)	(0.001)	(0.005)	(0.002)	(0.002)
GDD	-0.003***	0.001***	-0.000	0.007***	0.002***	-0.002***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Precipitation	-0.043***	-0.001***	0.009***	-0.064***	-0.001	0.017***
	(0.002)	(0.000)	(0.001)	(0.003)	(0.001)	(0.002)
Precipitation sq.	0.000***	0.000*	0.000	0.000***	-0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
State-specific trend	Yes	Yes	Yes	Yes	Yes	Yes
County-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28878	28857	28857	28878	28851	28878
Adjusted R^2	0.290	0.108	0.124	0.273	0.106	0.148

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

Table S13. The effect of landscape configurational complexity (Mean Patch Area) on weather-related crop insurance losses: Linear fixed effects model with state-specific trend and irrigation variables

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Mean Patch Area	0.085	0.046***	-0.503***	-0.217*	0.066***	-1.081***
	(0.071)	(0.010)	(0.050)	(0.118)	(0.017)	(0.100)
HDD	0.090***	0.014***	0.000	0.086**	0.020***	0.006**
	(0.004)	(0.001)	(0.001)	(0.005)	(0.002)	(0.002)
GDD	-0.003***	0.001***	-0.000	0.007***	0.002***	-0.002***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Precipitation	-0.043***	-0.001***	0.009***	-0.064***	-0.001	0.017***
	(0.002)	(0.000)	(0.001)	(0.003)	(0.001)	(0.002)
Precipitation sq.	0.000***	0.000*	0.000	0.000***	-0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Irrigation	0.010**	-0.000	0.002	0.006	0.000	-0.006
	(0.004)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
State-specific trend	Yes	Yes	Yes	Yes	Yes	Yes
County-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28878	28857	28857	28878	28851	28878
Adjusted R^2	0.290	0.108	0.124	0.273	0.106	0.148

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

Table S14. The effect of landscape configurational complexity (Mean Patch Area) on weather-related crop insurance losses in counties east of the 100th meridian: Linear fixed effects model with state-specific trend

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Mean Patch Area	0.270***	0.061***	-0.598***	0.142	0.097***	-1.393***
	(0.063)	(0.011)	(0.055)	(0.123)	(0.020)	(0.109)
HDD	0.108***	0.019***	0.000	0.144***	0.030***	-0.001
	(0.005)	(0.002)	(0.002)	(0.007)	(0.002)	(0.003)
GDD	-0.003***	0.000	-0.000	0.003**	0.000	-0.002**
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Precipitation	-0.044***	0.000	0.005**	-0.080***	0.000	0.018***
	(0.003)	(0.001)	(0.002)	(0.004)	(0.001)	(0.004)
Precipitation sq.	0.000***	-0.000	0.000	0.000***	-0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
State-specific trend	Yes	Yes	Yes	Yes	Yes	Yes
County-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18866	18866	18866	18866	18866	18866
Adjusted R^2	0.364	0.140	0.163	0.373	0.160	0.203

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

Table S15. The effect of landscape configurational complexity (Mean Patch Area) on weather-related crop insurance losses: Linear fixed effects model with year fixed and county fixed effects

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Mean Patch Area	0.019	0.033***	-0.504***	-0.306***	0.046***	-1.138***
	(0.068)	(0.010)	(0.049)	(0.113)	(0.018)	(0.102)
HDD	0.105***	0.015***	0.006***	0.101***	0.020***	0.024***
	(0.004)	(0.001)	(0.001)	(0.006)	(0.002)	(0.003)
GDD	0.005***	0.000**	-0.002***	0.017***	0.001***	-0.006***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Precipitation	-0.029***	-0.001***	0.005***	-0.043***	-0.000	0.010***
	(0.002)	(0.000)	(0.001)	(0.003)	(0.001)	(0.003)
Precipitation sq.	0.000***	0.000**	0.000***	0.000***	-0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28878	28857	28857	28878	28851	28878
Adjusted R^2	0.308	0.104	0.135	0.289	0.100	0.159

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

Table S16. The effect of landscape configurational complexity (Mean Patch Area) on weather-related crop insurance losses: Linear fixed effects model with year fixed effects, county fixed effects, and irrigation variable

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Mean Patch Area	0.020	0.033***	-0.503***	-0.306***	0.046***	-1.137***
	(0.068)	(0.010)	(0.049)	(0.113)	(0.018)	(0.102)
HDD	0.105***	0.015***	0.006***	0.101***	0.020***	0.024***
	(0.004)	(0.001)	(0.001)	(0.006)	(0.002)	(0.003)
GDD	0.005***	0.000**	-0.002***	0.017***	0.001***	-0.006***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Precipitation	-0.029***	-0.001***	0.005***	-0.043***	-0.000	0.010***
	(0.002)	(0.000)	(0.001)	(0.003)	(0.001)	(0.003)
Precipitation sq.	0.000***	0.000**	0.000***	0.000***	-0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Irrigation	0.019***	0.000	0.006***	0.023***	0.001	0.014**
	(0.005)	(0.001)	(0.002)	(0.007)	(0.003)	(0.006)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28878	28857	28857	28878	28851	28878
Adjusted R^2	0.309	0.104	0.135	0.289	0.100	0.159

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

Table S17. The effect of landscape configurational complexity (Mean Patch Area) on weather-related crop insurance losses (in counties east of the 100th meridian): Linear fixed effects model with year fixed and county fixed effects

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Mean Patch Area	0.196***	0.045***	-0.617***	0.087	0.078***	-1.444***
	(0.056)	(0.011)	(0.052)	(0.106)	(0.021)	(0.109)
HDD	0.126***	0.020***	0.006***	0.157***	0.030***	0.034***
	(0.005)	(0.002)	(0.002)	(0.007)	(0.002)	(0.004)
GDD	0.018***	-0.000	-0.003***	0.037***	-0.001**	-0.011***
	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.002)
Precipitation	-0.024***	0.000	0.002	-0.047***	0.001	0.008*
	(0.003)	(0.001)	(0.002)	(0.004)	(0.001)	(0.004)
Precipitation sq.	0.000***	-0.000	0.000***	0.000***	-0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18866	18866	18866	18866	18866	18866
Adjusted R^2	0.404	0.138	0.183	0.413	0.158	0.227

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

Table S18. The effect of landscape configurational complexity (Mean Patch Area) on weather-related crop insurance losses: Linear fixed effects model with crop share measures

	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
MPA	0.642***	0.051***	-0.557***	0.954***	0.067**	-1.152***
	(0.098)	(0.017)	(0.076)	(0.153)	(0.030)	(0.137)
HDD	0.138***	0.024***	-0.008***	0.221***	0.041***	-0.011**
	(0.008)	(0.002)	(0.002)	(0.012)	(0.002)	(0.005)
GDD	-0.008***	-0.001***	0.001	-0.010***	-0.002***	-0.002*
	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.001)
Precipitation	-0.054***	-0.003**	0.007***	-0.107***	-0.004***	0.015***
	(0.005)	(0.001)	(0.003)	(0.007)	(0.001)	(0.005)
Precipitation sq.	0.000***	0.000**	0.000	0.000***	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Corn share	6.924***	1.519***	1.160	12.350***	2.090***	-1.756
	(2.598)	(0.326)	(1.423)	(4.186)	(0.525)	(2.399)
Soybean share	-3.425*	-0.210	1.122	-5.235	-0.330	4.692*
	(1.897)	(0.230)	(1.710)	(3.247)	(0.380)	(2.539)
Wheat share	0.409	-0.047	0.370	0.380	-0.026	0.259
	(0.387)	(0.030)	(0.247)	(0.687)	(0.048)	(0.360)
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7902	7902	7902	7902	7902	7902
Adjusted R^2	0.445	0.271	0.130	0.468	0.309	0.158

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

Table S19. The effect of landscape configurational complexity (Mean Patch Area) on crop insurance loss for corn: Linear fixed effects models

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Mean Patch Area	0.450***	0.075***	-0.522***	0.344**	0.064*	-1.004***
	(0.107)	(0.023)	(0.057)	(0.154)	(0.038)	(0.134)
HDD	0.105***	0.035***	0.007***	0.131***	0.056***	0.027***
	(0.006)	(0.002)	(0.002)	(0.008)	(0.003)	(0.004)
GDD	-0.001	-0.002***	-0.004***	0.003*	-0.003***	-0.005***
	(0.001)	(0.000)	(0.001)	(0.002)	(0.001)	(0.001)
Precipitation	-0.038***	-0.005***	0.007***	-0.068***	-0.010***	0.018***
	(0.004)	(0.001)	(0.003)	(0.005)	(0.002)	(0.004)
Precipitation sq.	0.000***	0.000***	0.000*	0.000***	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28061	20025	20025	28061	20025	28061
Adjusted R^2	0.105	0.132	0.099	0.164	0.143	0.041

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

Table S20. The effect of landscape configurational complexity (Mean Patch Area) on crop insurance loss for soybeans: Linear fixed effects models

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Mean Patch Area	0.186**	-0.021	-0.421***	0.038	-0.030	-0.690***
	(0.089)	(0.020)	(0.043)	(0.112)	(0.034)	(0.121)
HDD	0.076***	0.029***	-0.015***	0.114***	0.053***	0.010**
	(0.005)	(0.003)	(0.003)	(0.007)	(0.004)	(0.004)
GDD	-0.001	-0.002***	-0.002***	0.001	-0.003***	-0.005***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Precipitation	-0.007*	-0.005***	0.002	-0.025***	-0.008***	0.012***
	(0.003)	(0.001)	(0.004)	(0.004)	(0.002)	(0.004)
Precipitation sq.	0.000	0.000***	0.000**	0.000	0.000***	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28052	17508	17508	28052	17508	28052
Adjusted R^2	0.062	0.074	0.096	0.129	0.108	0.029

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

Table S21. The effect of landscape configurational complexity (Mean Patch Area) on crop insurance loss for wheat: Linear fixed effects models

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Mean Patch Area	-0.434***	-0.029***	-0.144	-0.613***	-0.075***	-0.150
	(0.139)	(0.009)	(0.101)	(0.161)	(0.024)	(0.156)
HDD	0.015***	-0.002***	-0.010**	0.015**	-0.004***	-0.008
	(0.005)	(0.000)	(0.004)	(0.006)	(0.001)	(0.006)
GDD	-0.000	0.001***	0.028***	-0.000	0.002***	0.039***
	(0.001)	(0.000)	(0.002)	(0.002)	(0.000)	(0.002)
Precipitation	-0.047***	-0.001***	0.031***	-0.076***	-0.003***	0.042***
	(0.005)	(0.000)	(0.004)	(0.006)	(0.001)	(0.004)
Precipitation sq.	0.000***	0.000***	-0.000***	0.000***	0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28057	19297	19297	28057	19297	28057
Adjusted R^2	0.012	0.003	0.063	0.025	0.004	0.038

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

Table S22. The effect of landscape configurational complexity (Mean Patch Area) on weather-related crop insurance losses:

Correlated random effects (CRE) model

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Mean Patch Area	0.051	0.039***	-0.769***	-0.237**	0.053***	-1.214***
	(0.073)	(0.011)	(0.055)	(0.108)	(0.019)	(0.086)
HDD	0.027***	0.005***	-0.004***	0.040***	0.011***	-0.005*
	(0.002)	(0.000)	(0.001)	(0.004)	(0.001)	(0.003)
GDD	0.004***	0.002***	-0.001**	0.009***	0.002***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Precipitation	-0.014***	0.000	0.020***	-0.029***	0.001***	0.038***
	(0.002)	(0.000)	(0.001)	(0.003)	(0.001)	(0.002)
Precipitation sq.	-0.000	-0.000**	-0.000***	-0.000	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
County-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28878	28857	28857	28878	28851	28878

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

Table S23. The effect of landscape configurational complexity (Mean Patch Area) on crop insurance losses: Moment-based IV model

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Mean Patch Area	0.547***	0.121***	-0.289***	0.265	0.171***	-0.582***
	(0.146)	(0.033)	(0.076)	(0.239)	(0.050)	(0.144)
HDD	0.090***	0.014***	-0.000	0.086***	0.020***	0.007***
	(0.004)	(0.001)	(0.001)	(0.005)	(0.002)	(0.002)
GDD	-0.003***	0.001***	-0.000	0.008***	0.002***	-0.002***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Precipitation	-0.043***	-0.001***	-0.009***	-0.063***	-0.001	0.018***
	(0.002)	(0.000)	(0.001)	(0.003)	(0.001)	(0.002)
Precipitation sq.	0.000***	0.000*	0.000	0.000***	-0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
State-specific trend	Yes	Yes	Yes	Yes	Yes	Yes
County-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28878	28857	28857	28878	28851	28878
Adjusted R^2	0.211	0.010	0.028	0.193	0.008	0.054
AIC	192530.341	109929.166	164363.669	217645.177	132087.357	201287.577
BIC	192968.695	110367.481	164801.984	218083.531	132525.662	201725.932
Kleibergen-Paap rk LM statistic	352.684	352.451	352.451	352.668	352.205	352.508
	($p = 0.000$)	($p = 0.000$)	($p = 0.000$)	($p = 0.000$)	($p = 0.000$)	($p = 0.000$)
Kleibergen-Paap rk Wald F statistic	44.823	44.790	44.790	44.821	44.780	44.813
(Stock-Yogo 25% max)	37.04	37.04	37.04	37.04	37.04	37.04
Hansen J statistic	241.937	164.192	296.799	265.162	242.160	347.789
	($p = 0.000$)	($p = 0.000$)	($p = 0.000$)	($p = 0.000$)	($p = 0.000$)	($p = 0.000$)

Notes: (i) *** p < 0.01, ** p < 0.05, * p < 0.1. (ii) Standard errors are in parentheses. (iii) The Kliebergen-Paap rk LM stat, Kliebergen-Paap rk Wald stat, and Hansen J stat are diagnostic tests that aim to help assess the appropriateness of the IVs. (iv) The BP test rejects the null hypothesis of homoscedasticity (i.e., BP test statistic is 1433.09 and the p-value is 0.000).

Table S24. The effect of landscape compositional complexity (Shannon Diversity Index) on crop insurance loss: Kinky least squared regressions (correlation = 0.1)

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Shannon Diversity Index	-5.083***	-0.536***	-0.049	-6.511***	-0.585***	-1.041***
	(0.130)	(0.038)	(0.076)	(0.193)	(0.048)	(0.144)
HDD	0.034***	0.002***	0.004***	0.016***	0.002***	-0.001
	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.001)
GDD	0.000	0.000***	-0.001***	0.003***	0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	0.001	-0.000***	0.004***	0.004***	-0.001***	0.011***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Precipitation sq.	-0.000***	-0.000**	0.000***	-0.000***	-0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	29486	29464	29464	29486	29458	29486

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

Table S25. The effect of landscape compositional complexity (Shannon Diversity Index) on crop insurance loss: Kinky least squared regressions (correlation = 0.2)

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Shannon Diversity Index	-7.383***	-1.021***	-1.362***	-9.999***	-1.318***	-3.614***
	(0.147)	(0.060)	(0.090)	(0.209)	(0.068)	(0.160)
HDD	0.034***	0.002***	0.003***	0.014***	0.001***	-0.002
	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.001)
GDD	0.000	0.000***	-0.001***	0.003***	0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	-0.002***	-0.001***	0.002***	-0.001	-0.002***	0.008***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Precipitation sq.	-0.000***	-0.000	0.000***	-0.000***	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	29486	29464	29464	29486	29458	29486

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

Table S26. The effect of landscape compositional complexity (Shannon Diversity Index) on crop insurance loss: Kinky least squared regressions (correlation = 0.3)

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Shannon Diversity Index	-9.849***	-1.541***	-2.769***	-13.738***	-2.103***	-6.372***
	(0.172)	(0.084)	(0.109)	(0.236)	(0.091)	(0.186)
HDD	0.033***	0.002***	0.003***	0.013***	0.001***	-0.003**
	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.002)
GDD	0.001***	0.000***	-0.001***	0.003***	0.001***	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	-0.006***	-0.002***	0.000	-0.006***	-0.003***	0.004***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Precipitation sq.	-0.000***	0.000**	0.000***	-0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	29486	29464	29464	29486	29458	29486

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

Table S27. The effect of landscape compositional complexity (Shannon Diversity Index) on crop insurance loss: Kinky least squared regressions (correlation = 0.4)

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Shannon Diversity Index	-12.602***	-2.122***	-4.340***	-17.914***	-2.980***	-9.451***
	(0.205)	(0.105)	(0.132)	(0.277)	(0.114)	(0.221)
HDD	0.032***	0.002***	0.002***	0.012***	0.001*	-0.004***
	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.002)
GDD	0.001***	0.000***	-0.000***	0.004***	0.001***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	-0.009***	-0.003***	-0.002***	-0.011***	-0.004***	0.000
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Precipitation sq.	-0.000***	0.000***	0.000***	-0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	29486	29464	29464	29486	29458	29486

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

Table S28. The effect of landscape compositional complexity (Shannon Diversity Index) on crop insurance loss: Kinky least squared regressions (correlation = 0.5)

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Shannon Diversity Index	-15.836***	-2.805***	-6.186***	-22.819***	-4.010***	-13.068***
	(0.248)	(0.121)	(0.160)	(0.341)	(0.133)	(0.270)
HDD	0.031***	0.002***	0.002*	0.010***	0.000	-0.006***
	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.002)
GDD	0.001***	0.000***	-0.000*	0.005***	0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	-0.014***	-0.003***	-0.004***	-0.018***	-0.006***	-0.004***
	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.001)
Precipitation sq.	-0.000	0.000***	0.000***	-0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	29486	29464	29464	29486	29458	29486

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

Table S29. The effect of landscape compositional complexity (Shannon Diversity Index) on crop insurance loss: Kinky least squared regressions (correlation = 0.6)

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Shannon Diversity Index	-19.907***	-3.663***	-8.510***	-28.993***	-5.307***	-17.621***
	(0.317)	(0.126)	(0.196)	(0.457)	(0.146)	(0.351)
HDD	0.029***	0.001***	0.001	0.008***	-0.000	-0.007***
	(0.002)	(0.000)	(0.001)	(0.002)	(0.001)	(0.002)
GDD	0.002***	0.001***	0.000	0.005***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	-0.019***	-0.005***	-0.007***	-0.026***	-0.007***	-0.010***
	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.001)
Precipitation sq.	0.000**	0.000***	0.000***	-0.000	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	29486	29464	29464	29486	29458	29486

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

Table S30. The effect of landscape compositional complexity (Shannon Diversity Index) on crop insurance loss: Kinky least squared regressions (correlation = 0.7)

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Shannon Diversity Index	-25.591***	-4.863***	-11.754***	-37.614***	-7.117***	-23.979***
	(0.470)	(0.106)	(0.270)	(0.711)	(0.155)	(0.526)
HDD	0.027***	0.001**	-0.000	0.004	-0.001	-0.010***
	(0.002)	(0.000)	(0.001)	(0.003)	(0.001)	(0.002)
GDD	0.003***	0.001***	0.000***	0.006***	0.001***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	-0.026***	-0.006***	-0.011***	-0.037***	-0.010***	-0.019***
	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.002)
Precipitation sq.	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	29486	29464	29464	29486	29458	29486

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

Table S31. The effect of landscape compositional complexity (Shannon Diversity Index) on crop insurance loss: Kinky least squared regressions (correlation = 0.8)

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Shannon Diversity Index	-35.168***	-6.884	-17.221***	-52.137***	-10.168***	-34.690***
	(0.955)	(.)	(0.521)	(1.471)	(0.226)	(1.068)
HDD	0.024***	0.000	-0.002*	-0.001	-0.002**	-0.013***
	(0.002)	(0.000)	(0.001)	(0.004)	(0.001)	(0.003)
GDD	0.004***	0.001***	0.001***	0.008***	0.002***	0.003***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Precipitation	-0.039***	-0.009***	-0.019***	-0.056***	-0.014***	-0.033***
	(0.002)	(0.000)	(0.001)	(0.003)	(0.001)	(0.002)
Precipitation sq.	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	29486	29464	29464	29486	29458	29486

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

Table S32. The effect of landscape compositional complexity (Shannon Diversity Index) on crop insurance loss: Kinky least squared regressions (correlation = 0.9)

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Shannon Diversity Index	-61.779***	-12.500***	-32.412***	-92.496***	-18.645***	-64.453***
	(4.537)	(0.788)	(2.547)	(6.904)	(1.332)	(5.064)
HDD	0.014***	-0.002**	-0.008***	-0.016**	-0.005***	-0.024***
	(0.004)	(0.001)	(0.002)	(0.006)	(0.001)	(0.005)
GDD	0.007***	0.002***	0.003***	0.013***	0.003***	0.007***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Precipitation	-0.074***	-0.016***	-0.039***	-0.110***	-0.025***	-0.072***
	(0.007)	(0.001)	(0.004)	(0.010)	(0.002)	(0.007)
Precipitation sq.	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	29486	29464	29464	29486	29458	29486

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

Table S33. The effect of landscape configurational complexity (Mean Patch Area) on crop insurance loss: Kinky least squared regressions (correlation = -0.1)

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Mean Patch Area	0.358***	0.062***	-0.015	0.602***	0.096***	0.169***
	(0.021)	(0.006)	(0.012)	(0.032)	(0.008)	(0.023)
HDD	0.036***	0.003***	0.004***	0.017***	0.002***	-0.002
	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.001)
GDD	-0.000	0.000***	-0.001***	0.002***	0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	0.006***	-0.000	0.004***	0.010***	-0.001***	0.012***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Precipitation sq.	-0.000***	-0.000***	0.000***	-0.000***	-0.000*	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	28878	28857	28857	28878	28851	28878

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

Table S34. The effect of landscape configurational complexity (Mean Patch Area) on crop insurance loss: Kinky least squared regressions (correlation = -0.2)

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Mean Patch Area	0.723***	0.139***	0.192***	1.152***	0.210***	0.574***
	(0.024)	(0.010)	(0.015)	(0.035)	(0.011)	(0.026)
HDD	0.035***	0.002***	0.003***	0.016***	0.002***	-0.003*
	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.001)
GDD	0.000	0.000***	-0.001***	0.003***	0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	0.005***	-0.000*	0.003***	0.008***	-0.001***	0.011***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Precipitation sq.	-0.000***	-0.000**	0.000***	-0.000***	-0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	28878	28857	28857	28878	28851	28878

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

Table S35. The effect of landscape configurational complexity (Mean Patch Area) on crop insurance loss: Kinky least squared regressions (correlation = -0.3)

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Mean Patch Area	1.113***	0.221***	0.413***	1.739***	0.333***	1.006***
	(0.029)	(0.013)	(0.018)	(0.040)	(0.015)	(0.031)
HDD	0.034***	0.002***	0.003***	0.015***	0.001***	-0.003**
	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.002)
GDD	0.001***	0.000***	-0.000***	0.004***	0.001***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	0.003***	-0.001***	0.003***	0.005***	-0.002***	0.009***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Precipitation sq.	-0.000***	-0.000	0.000***	-0.000***	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	28878	28857	28857	28878	28851	28878

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

Table S36. The effect of landscape configurational complexity (Mean Patch Area) on crop insurance loss: Kinky least squared regressions (correlation = -0.4)

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Mean Patch Area	1.545***	0.312***	0.658***	2.390***	0.469***	1.486***
	(0.035)	(0.017)	(0.022)	(0.047)	(0.018)	(0.037)
HDD	0.033***	0.002***	0.002***	0.013***	0.001**	-0.004***
	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.002)
GDD	0.001***	0.000***	-0.000*	0.005***	0.001***	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	0.001	-0.001***	0.002***	0.003**	-0.002***	0.007***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Precipitation sq.	-0.000***	0.000	0.000***	-0.000***	0.000**	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	28878	28857	28857	28878	28851	28878

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

Table S37. The effect of landscape configurational complexity (Mean Patch Area) on crop insurance loss: Kinky least squared regressions (correlation = -0.5)

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Mean Patch Area	2.049***	0.417***	0.943***	3.149***	0.627***	2.044***
	(0.043)	(0.020)	(0.027)	(0.059)	(0.022)	(0.046)
HDD	0.032***	0.002***	0.002**	0.012***	0.001	-0.005***
	(0.002)	(0.000)	(0.001)	(0.002)	(0.000)	(0.002)
GDD	0.002***	0.001***	0.000	0.005***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	-0.000	-0.001***	0.001	0.000	-0.003***	0.005***
	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.001)
Precipitation sq.	-0.000***	0.000**	0.000***	-0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	28878	28857	28857	28878	28851	28878

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

Table S38. The effect of landscape configurational complexity (Mean Patch Area) on crop insurance loss: Kinky least squared regressions (correlation = -0.6)

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Mean Patch Area	2.673***	0.548***	1.296***	4.089***	0.823***	2.736***
	(0.055)	(0.021)	(0.033)	(0.078)	(0.024)	(0.060)
HDD	0.031***	0.002***	0.001	0.010***	0.000	-0.007***
	(0.002)	(0.000)	(0.001)	(0.002)	(0.001)	(0.002)
GDD	0.003***	0.001***	0.001***	0.007***	0.001***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	-0.003**	-0.002***	-0.001	-0.003**	-0.004***	0.003**
	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.001)
Precipitation sq.	-0.000***	0.000***	0.000***	-0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	28878	28857	28857	28878	28851	28878

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

Table S39. The effect of landscape configurational complexity (Mean Patch Area) on crop insurance loss: Kinky least squared regressions (correlation = -0.7)

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Mean Patch Area	3.521***	0.726***	1.777***	5.366***	1.090***	3.677***
	(0.078)	(0.017)	(0.044)	(0.117)	(0.025)	(0.086)
HDD	0.029***	0.001***	0.000	0.008***	-0.000	-0.009***
	(0.002)	(0.000)	(0.001)	(0.003)	(0.001)	(0.002)
GDD	0.004***	0.001***	0.001***	0.008***	0.002***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Precipitation	-0.006***	-0.003***	-0.003***	-0.008***	-0.005***	-0.001
	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.001)
Precipitation sq.	-0.000**	0.000***	0.000***	-0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	28878	28857	28857	28878	28851	28878

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

Table S40. The effect of landscape configurational complexity (Mean Patch Area) on crop insurance loss: Kinky least squared regressions (correlation = -0.8)

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Mean Patch Area	4.873***	1.010	2.543***	7.403***	1.515***	5.176***
	(0.135)	(.)	(0.074)	(0.208)	(0.029)	(0.150)
HDD	0.027***	0.001	-0.001	0.004	-0.001	-0.012***
	(0.002)	(0.000)	(0.001)	(0.003)	(0.001)	(0.003)
GDD	0.005***	0.001***	0.002***	0.010***	0.002***	0.005***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Precipitation	-0.011***	-0.004***	-0.005***	-0.016***	-0.006***	-0.007***
	(0.002)	(0.000)	(0.001)	(0.002)	(0.000)	(0.002)
Precipitation sq.	0.000	0.000***	0.000***	-0.000	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	28878	28857	28857	28878	28851	28878

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

Table S41. The effect of landscape configurational complexity (Mean Patch Area) on crop insurance loss: Kinky least squared regressions (correlation = -0.9)

	LCR			LAR		
	LCR_Drought	LCR_Heat	LCR_Moisture	LAR_Drought	LAR_Heat	LAR_Moisture
Mean Patch Area	7.992***	1.665***	4.309***	12.102***	2.495***	8.636***
	(0.375)	(0.012)	(0.209)	(0.570)	(0.089)	(0.412)
HDD	0.021***	-0.001	-0.005**	-0.006	-0.003***	-0.018***
	(0.003)	(0.001)	(0.002)	(0.005)	(0.001)	(0.004)
GDD	0.009***	0.002***	0.004***	0.016***	0.003***	0.009***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Precipitation	-0.023***	-0.006***	-0.012***	-0.034***	-0.010***	-0.020***
	(0.003)	(0.000)	(0.001)	(0.004)	(0.001)	(0.003)
Precipitation sq.	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	28878	28857	28857	28878	28851	28878

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