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The causal effect of agricultural landscape simplification on Germany's grasslands during a compound drought and heatwave in 2018

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ABSTRACT

Preserving ecosystem services and economic and environmental benefits will require future landscape policies to identify and incorporate specific landscape features. In this paper we define the term, agricultural landscape simplification, as the reduced compositional and configurational heterogeneity characterized by lower diversity and smaller numbers, sizes, and simpler arrangements of agricultural land uses, which can impair multiple regulating ecosystem services. To examine the causal effects of agricultural landscape simplification on grassland drought impact, we derive a novel remote-sensing product to measure spatial variation in the impact of drought in grasslands during a prolonged drought and heatwave in 2018, and relate it to a multidimensional index of landscape simplification based on landscape metrics. Our causal identification strategy relies on a spatially explicit fuzzy Regression Discontinuity Design (RDD) and uses Germany's former inner border as an exogenous predictor of agricultural landscape simplification intensity. We identify that a 10 % increase in agricultural landscape simplification is associated with a 7 % increase in grassland drought impact at the former inner border, and quantify the potential forgone revenues associated with the decrease in grassland productivity at approximately 52 € per ha. Our results suggest that identifying the full range of agricultural landscape simplification’s adverse environmental and economic effects would improve preventive landscape policy designs enhancing drought resistance and fostering climate change adaptation strategies.

Keywords: Drought, Grassland, Landscape Simplification, Former Inner German Border, Fuzzy RDD

JEL-codes: Q54, Q15

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1 | INTRODUCTION

Global warming increases weather risks for agricultural production, with adverse effects on ecosystem functioning, mainly due to the increased frequency and magnitude of extreme hydro-meteorological events (Mendelsohn, Nordhaus and Shaw 1994; Gornall et al. 2010; Malhi, Kaur and Kaushik 2021; Shukla et al. 2019). Compound drought and heatwave events in particular disturb the water cycle and climate regulating functions of land ecosystems, and compromise the preservation of ecosystem services and economic and environmental benefits including agricultural yields (Santini et al. 2022; Cuevas, Pek and Salman 2024). In Germany, our study region, droughts were responsible for the highest monetary losses between 1995 and 2019 within the agricultural sector (Schmitt et al. 2022). Intensive land management, larger field sizes, and the simplification of agricultural landscapes have been noted as possible causes of a reduced capacity to cope with climate extremes, which makes simplified agricultural landscapes more susceptible to extreme hydroclimatic events (Guo et al. 2023; Peng et al. 2019; Levia et al. 2020; McCarthy et al. 2021).

Previous research suggests a link between agricultural landscape simplification in eastern Germany and related susceptibility to droughts (Vogel, Scherer-Lorenzen and Weigelt 2012; Schmitt et al. 2024). However, a causal link was not established yet, despite previous studies using quasi-experimental designs at the former inner German border to quantify the causal effects of farm and field size structure on bird diversity (Noack et al. 2022), environmental friendliness of farming (Wuepper, Wimmer and Sauer 2020), and biodiversity-profit trade-offs (Batáry et al. 2017).

This paper closes this gap by quantifying the causal effect of agricultural landscape simplification on grassland drought-related damages during a compound drought and heatwave in Germany. We hypothesize that the lack of compositional and configuration heterogeneity reduces grassland functionality and drought resistance. Our quasi-experimental research design leverages the history-induced, and thus exogenous, discontinuous variation in agricultural landscape composition and configuration between the western and eastern parts of the former inner German border. Specifically, we use a fuzzy Regression Discontinuity Design (fuzzy RDD) to estimate the causal effect of agricultural landscape simplification on the state of embedded grasslands under the compound drought and heatwave conditions in 2018 (Zscheischler and Fischer 2020). We use a novel index capturing grasslands' damage based on high-resolution remote-sensing data, create a composite index of landscape simplification based on the Shannon Diversity Index and Edge Density, and include several contextual variables for land cover, bioclimate, topography, soil texture, grassland use intensity, and ecological conservation policies in the region. We then employ a biophysical growth model to quantify the forgone revenues resulting from the decrease in grassland productivity due to agricultural landscape simplification.

We find that a 10 % increase in agricultural landscape simplification leads to a 7 % rise in grassland drought impact at the former inner German border. The forgone revenues associated with a 10 % increase in landscape simplification on the eastern side of the border is on average 52 € per ha.

This paper makes three important contributions to the agricultural and climate change economics literature. To our knowledge, this is the first research that causally attributes landscape simplification to drought effects on grassland functionality. Second, we demonstrate that promoting compositional and configurational heterogeneity in agricultural landscapes provides both environmental benefits and economic returns that potentially can offset some of the losses associated with reduced economies of scale. Third, by relying on a rigorous identification strategy and using novel data products from several disciplines, we demonstrate the necessity and relevance of interdisciplinary research.

The remainder of this paper is organized as follows: Section 2 outlines the historical events affecting the agricultural landscape structures in eastern and western Germany, and introduces our hypothesis. Section 3 explains our empirical approach, and Section 4 describes our dataset.

Section 5 validates our identification strategy. Section 6 gives the results and Section 7 explores the economic implications of our findings. Section 8 concludes with policy implications and directions for future research.

2 | BACKGROUND AND IDENTIFICATION STRATEGY

2.1 Background

Agricultural landscapes with large fields, land use homogenization, and large-scale farming structures still persist in eastern Germany given Germany's history of expropriation and land collectivization after 1945 (Wolz 2013). By 2018, about 15,967 farms operated on 33,200 ha in eastern Germany, and 153,041 farms operated on 57,493 ha in western Germany. The average farm size was 225.0 ha in eastern Germany and 29.1 ha in western Germany (Jänicke et al. 2024). In 2023 in the federal state of Brandenburg, agricultural holdings and cooperatives, the successors of typical socialistic collective farms, operated on 704 ha on average, and about one-fifth of Brandenburg's farms cultivated 55.6 % of the farmland with an average field size of 12 ha (Wesemeyer et al. 2023).

Larger farms can reduce land use diversity both in space and over time due to economies of scale (Batáry et al. 2017; Ricciardi et al. 2021). As in many post-transition regions, field sizes increased in eastern Germany during the consolidation process (Samberg et al. 2016; Lesiv et al. 2019), whereas smaller farms maintained land use diversity, i.e., landscape heterogeneity and higher ecosystem functionality, in western Germany (Wuepper et al. 2020; Seifert, Wolff and Hüttel 2024). As a result, notable differences in the composition and configuration of agricultural landscapes between eastern and western Germany prevail (see Figure 1), with less heterogeneous landscapes in eastern Germany also associated with much higher drought stress-induced yield losses compared to the rest of the country (Riedesel et al. 2023; Schmitt et al. 2024).

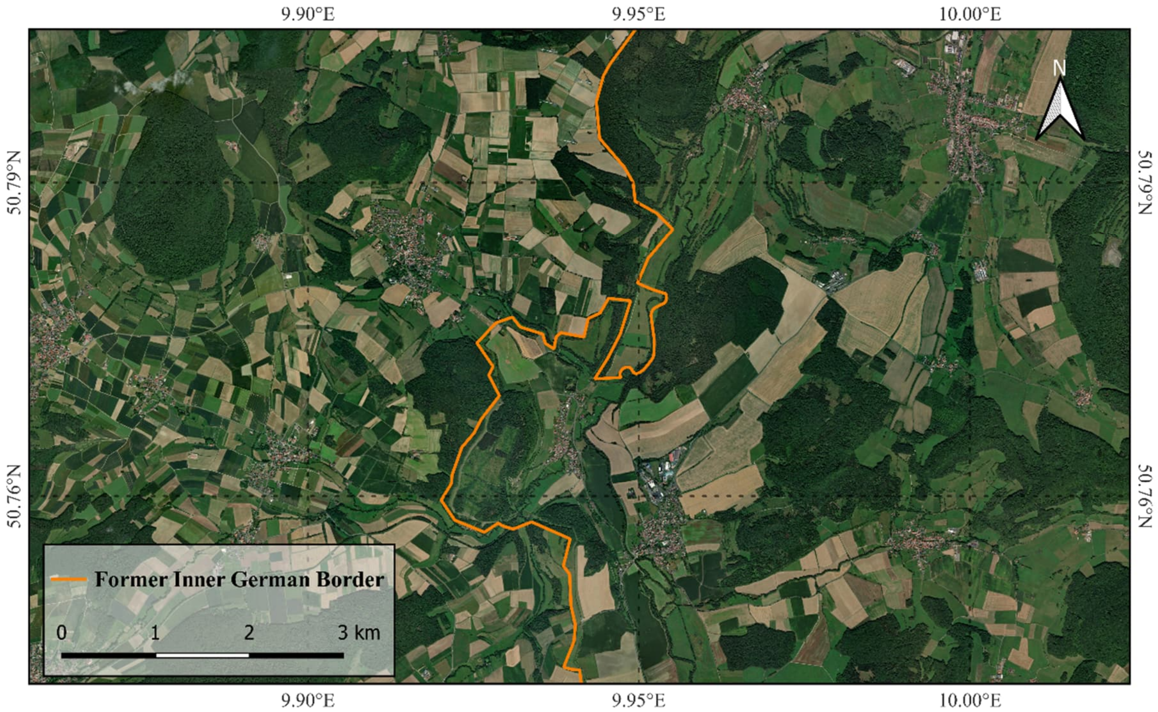

FIGURE 1 Satellite image (ESRI World Imagery) of agricultural landscapes at the former inner border (orange line); left: smaller fields and higher land use diversity in western Germany; right: larger fields and less diversity as a result of land collectivization reforms in eastern Germany, 1949–1989.

This triggered scientific debates about the reasons for the higher susceptibility of eastern German landscapes and farmland productivity to compound heatwave and drought events. A possible reason is the level of diversification in land use composition and configuration at the landscape scale (e.g., the proportion and spatial arrangements of wheat, grassland, orchard, small woody features, and other land uses) (Vogel et al. 2012; Molénat et al. 2023). Agricultural landscape simplification is a process that by decreasing land use diversification transforms agricultural landscapes into less biologically diverse ecosystems (Hufnagel, Reckling and Ewert 2020). Plant genetic, functional, and structural diversity of land uses within agricultural landscapes are important factors regulating plant competition and promoting the complementary and cooperative effects resulting from the ecological differences between plants (Barry et al. 2019). In grasslands, plant diversity appears to enhance biomass productivity similarly to other management practices such as increasing fertilization rates or mowing frequency (Schaub et al. 2020). Therefore, reductions in plant diversity can also increase susceptibility to extreme events such as droughts (Wang et al. 2025).

2.2 Identification Strategy

The historical division between eastern and western Germany provides a unique opportunity to develop a credible causal identification strategy. Our objective is to quantify the causal effects of agricultural landscape simplification on the impact of drought in grasslands. We recognize that causal identification can be challenging due to potential endogeneity from omitted variable bias and reverse causality. Omitted variable bias occurs when a third factor influences both landscape simplification and drought effects; for instance, if grassland mowing events induce more landscape simplification and more severe drought impact. Reverse causality occurs when drought impact influences landscape simplification directly. Quasi-experimental designs used to overcome these challenges, generally require certain assumptions to hold for causal inference.

If the historical division between eastern and western Germany was not based on environmental or topographic factors, we can observe conditions analogous to a natural experiment around the former inner German border, and compare observations from both sides similar to a randomized experiment. In the presence of a discontinuity in the outcome at the border, we can interpret the size of the discontinuity as a Local Average Treatment Effect (LATE)[1], where treatment status can depend, either completely or partly, on the geographical location of the observation. Accordingly, the literature distinguishes two types of RDD: sharp RDD, where treatment is assigned with a deterministic rule, in our paper being on one side or the other of the border, and fuzzy RDD, where the border either affects the probability of receiving the treatment, or as in our paper, induces variations in treatment intensity.

[1] LATE is a form of Average Treatment Effect (ATE) (Imbens and Angrist 1994).

Estimating an RDD model can use either parametric or nonparametric approaches. The parametric approach seeks to identify the optimal functional form that relates the outcome variable to the treatment variable across the entire dataset. The nonparametric approach treats the estimation of treatment effects as a local randomization experiment, and focuses the analysis on observations near the cut-off. By restricting the sample to datapoints near the cut-off, the nonparametric approach can reduce estimation bias, but it requires a sufficiently large sample size that allows narrower bandwidths without significantly compromising statistical power (Lee and Lemieux 2010).

3 | EMPIRICAL FRAMEWORK

Previous studies using RDD in a geographic setting use borders to define the cut-off between treated and control spatial units, but dividing treated and untreated groups at the cut-off can be overly rigid and lead to imperfect compliance with the treatment condition. We know that some agricultural landscapes in eastern Germany have low levels of compositional and configurational heterogeneity: Appendix A shows that agricultural landscapes in eastern Germany are on average more likely to have low compositional and configurational heterogeneity, but it is not a deterministic process. Therefore, we assume landscape simplification is a continuous treatment with a discontinuous break in its intensity at the border. To account for a change in treatment intensity at the cut-off, we apply a fuzzy RDD in a geographical setting and use the former inner German border as an instrumental variable that is employed as an exogenous predictor of a composite index for landscape simplification to account for the potentially endogenous treatment. Since comparisons between observations located at different latitudes and longitudes are likely to introduce endogeneity due to omitted variables (Keele and Titiunik 2015), we address the omitted variable problem by using an optimal bandwidth to include only observations near the border (Imbens and Kalyanaraman 2012), and by introducing border segment fixed effects analogous to a within estimator (Dell

2010). To generate border segment fixed effects, we discretize the border into three equally sized segments based on latitude, because we want to capture unobservable characteristics due to differences in terrain and climatic zones, i.e., mountains in the south, hills in the middle, and flat land in the north along the former inner border.

We use a two-stage least squares (2SLS) approach, i.e., in the first stage, we remove endogenous variation in the treatment variable by regressing it on an indicator variable for being located at the eastern part of the former inner German border:

$$LSI_{is} = \alpha_1 + f(running_{is}, East_{is}) + \delta_1 East_{is} + \beta_1 Z_{is} + \varphi_{1s} + \varepsilon_{is}, \tag{1}$$

where LSI_{is} measures the extent of landscape simplification in landscape i, located within border segment s, $f(running_{is}, East_{is})$ is a function of the running variable defining the distance of each observation to the closest point of the border, and the functional form is allowed to differ at the two sides of the border, $East_{is}$ is the indicator variable for eastern Germany that constitutes our instrument for landscape simplification in the fuzzy RDD setting, Z_{is} is a set of controls, φ_{1s} is a set of border segments fixed effects, and ε_{is} is the error term. In the second stage, we obtain the LATE by regressing the outcome variables on the predicted values of the treatment and further controls:

$$NDFI_{is} = \alpha_2 + f(running_{is}, East_{is}) + \delta_2 \widehat{LSI_{is}} + \beta_2 Z_{is} + \varphi_{2s} + \upsilon_{is}, \tag{2}$$

where $\widehat{LSI_{is}}$ denotes the predicted values of landscape simplification, $NDFI_{is}$ is the outcome for grassland drought impact, φ_{2s} is a set of border segments fixed effects, and υ_{is} is the error term, and coefficient δ_2 identifies the change in drought impact only due to the exogenous shift in the level of agricultural landscape simplification on the eastern side of the former inner German border.

To estimate both regression models, we use a local quadratic polynomial regression with a triangular kernel and optimal bandwidth selection based on the mean squared error (MSE) criterion (Calonico, Cattaneo and Titiunik 2014; Calonico, Cattaneo and Farrell 2020).

The inclusion of all controls in an additive manner allows us to decrease the variance of the estimates and check for potential mediators of the effects (Frölich and Huber 2019; Cattaneo, Keele and Titiunik 2022). More importantly, controls also help us to assess the sensitivity of our exclusion restriction within the fuzzy RDD. In order to fulfill the exclusion restriction, the main discontinuity at the border has to affect drought impact in grasslands through landscape simplification, and not through other factors. Thus, we will show that a host of other bioclimatic, topological, economic, and policy variables are continuous at the border and controlling for them does not affect our estimates.

4 | DATA

We use data within 50 km on both parts of the former inner border: an outcome metric capturing drought impact on grasslands based on a remote-sensing index, the Normalized Difference Fraction Index (NDFI), and landscape metrics to construct a composite index for agricultural landscape simplification for the treatment. The contextual variables we use for continuity checks and as control variables include bioclimatic conditions, land cover, elevation, soil texture, grassland use intensity, and areas of ecological networks. We harmonize the data at 1 x 1 km and include only agricultural landscapes with grassland.[2] The 1 x 1 km resolution is a compromise between a resolution that is wide enough to include several agricultural fields and narrow enough to have a sufficient number of non-transboundary observations close to the former inner German border. We remove observations with grid centroids located closer than

[2] Following Marshall (2004), we define agricultural landscapes as a mosaic of farmers' fields and only rely on grids with at least 10% of both grassland and cropland.

500 m from the border to eliminate trans-border observations. Our final dataset consists of 34,440 datapoints. At the end of Section 3, Table 1 reports the summary statistics explained below.

3.1 | Outcome Variable: Normalized Difference Fraction Index (NDFI)

To capture drought effects on grassland vegetation, we estimate drought metrics following an approach developed by Kowalski et al. (2022). These metrics are based on repeated Sentinel-2 observations within a year to model ground cover percentages of the main cover components of grasslands, namely green (photosynthetically active) vegetation, dry (non-photosynthetic) vegetation, and open soil. Based on the ground cover estimates, NDFI is calculated by contrasting dry vegetation and soil cover relative to the green vegetation cover. In Central European grasslands, sustained drought periods during the growing season trigger "shifts" in vegetation conditions towards decreasing green vegetation cover, whereas dry vegetation and soil cover increase (Kowalski, Okujeni and Hostert 2023; Kowalski et al. 2024). The NDFI quantifies the shifts, i.e., NDFI > 0 indicates predominantly dry vegetation and soil cover, and NDFI < 0 indicates predominantly green vegetation.

Unlike other common greenness-based vegetation indices such as the Normalized Difference Vegetation Index (NDVI), the NDFI allows a straightforward interpretation of the proportion of grassland that has become unsuitable for agricultural use due to droughts, making it easier to translate this information into economically relevant metrics such as biomass losses. We derive the NDFI mean from the 10 m ground cover time series available for all grasslands in Germany (Okujeni et al. 2024). We select all available 10 m Sentinel-2 observations from the growing season of 2018 to calculate our NDFI time series and interpolate them using Radial Basis Function Kernels to build an equidistant time series (Schwieder et al. 2016). Figure 2 shows the NDFI mean expressed in percentages of dry vegetation and soil cover.

We test the longest duration in number of days of NDFI > 0 as an alternative outcome. However, the model estimates do not lead to statistically significant results (Appendix D).

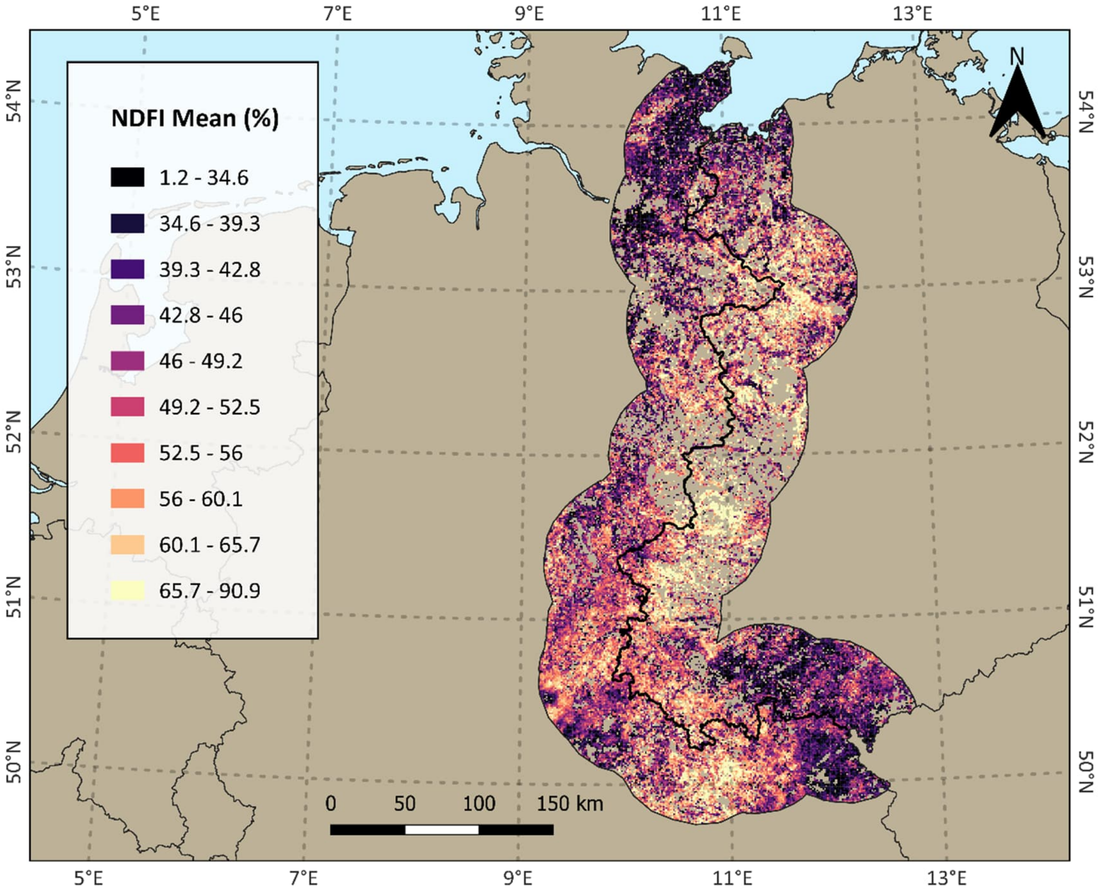

FIGURE 2 Landscape-level (1 x 1 km) distribution of the mean NDFI expressed as a percentage of dry grassland vegetation.
Note: Thick black line denotes the former inner border.

3.2 | Treatment Variable: Agricultural Landscape Simplification

Landscape metrics characterize landscapes in ecological frameworks, i.e., the algorithms quantify specific spatial characteristics of patches, classes of patches, or entire landscape mosaics (Uuemaa et al. 2009; Uuemaa, Mander and Marja 2013; Lausch et al. 2015). We calculate landscape metrics in 1 x 1 km landscapes for a dataset at 10 m resolution displaying the parcels' spatial distribution of 24 agricultural land uses in Germany (Blickensdörfer et al. 2022).[3]

[3] See Appendix D for a list of the crop classes in the data.

We use the Shannon Diversity Index (SHDI) to assess the level of compositional heterogeneity, instead of the Simpson's Diversity Index because the SHDI better represents compositional heterogeneity for landscape management within an ecological framework (Nagendra 2002). We calculate the SHDI as:

$$SHDI_i = -\sum_{j=1}^{m}(P_{ij}\, lnP_{ij}), \tag{3}$$

where the index for each geographical unit *i* is summed up over *m* different types of land uses ($m = 24$), j denotes each type of land use, and P_{ij} is the proportion of land use *j* in landscape *i*. The SHDI is zero when only one patch is present and increases, without a maximum, as the number of land uses increases when the proportions remain evenly distributed.

We complement the SHDI with Edge Density (ED) to assess landscape configurational heterogeneity.[4] We prefer it to other configurational metrics because the ED directly measures the level of spatial interaction between different land uses. As the ED increases, the number of patches increases, and patch size decreases (Wolff et al. 2021). The ED is equal to 0 when only one patch is present. We calculate it as:

$$ED_i = \frac{\sum_{k=1}^{m} e_{ijk}}{A_i}\, 10000, \tag{4}$$

where e_{ijk} is the edge length in m between land use *j* and all other land uses, $k \neq j$ in a given landscape *i*, *m* again denotes the number of different types of land uses, and A_i is the total landscape area multiplied by 10,000 to convert to ha.

We construct a continuous index of agricultural landscape simplification by combining the SHDI and ED into a composite index based on principal component analysis (PCA), so we can

[4] Liao et al. (2020) use both the SHDI and ED to study the effect of agricultural landscape composition and configuration on bird diversity and community structure.

construct a single metric that summarizes the information of both variables by extracting the first principal component (PC) containing the most information while minimizing noise. We calculate the index as:

$$LSI_{pc,i} = 1 - PC1_{norm,i} = 1 - \left(a_1 Z_{SHDI,i} + a_2 Z_{ED,i}\right)_{norm,i}, \quad (5)$$

where $LSI_{pc,i}$ is the landscape simplification index for landscape i, $PC1_{norm}$ is the normalized first PC, a_1 and a_2 are determined by the PCA based on the variance-covariance structure of the data, and $Z_{SHDI,i}$ and $Z_{ED,i}$ are the standardized values for the landscape metrics in landscape i.

We also construct another indicator that we test as an alternative treatment, i.e., a binary treatment that identifies simplified landscapes based on deterministic rules (see Appendix B).

3.3 | Set of Contextual Variables

We compile a set of contextual variables to validate our identification strategy and robustness checks. We use a land cover map (ELC10) (Venter and Sydenham 2021) at 10 m for 2018 to calculate the shares of broad land cover categories within each landscape: (1) artificial land, (2) cropland, (3) woodland, (4) shrubland, (5) grassland, (6) bare land, (7) water/permanent snow/ice, and (8) wetland.[5]

Since temperature and precipitation are the primary factors influencing the occurrence of droughts in grassland ecosystems (Sherry et al. 2008), we use data from the German Weather Service (DWD) stations (Kaspar et al. 2013). For temperature, we use the annual mean air

[5] ELC10 provides higher resolution and overall accuracy for the eight categories than CORINE (100 m) and similar land cover maps available for 2018.

temperature at 2 m aboveground, and for precipitation we use the annual sum of total precipitation.

Other key variables influence vegetation growth responses to drought, as well as average vegetation growth and survival. We use elevation data from the SRTM Digital Elevation Model for Germany. Each pixel of the SRTM X-SAR DEM has a resolution of 1 x 1 arcsecond on the ground corresponding approximately to 30 x 30 m. For soil composition, we use the percentage of clay and sand from a dataset at 500 m spatial resolution (Panagos et al. 2022). For management practices we use a dataset that identifies the number of mowing events annually (here, 2017 and 2018) at the parcel level based on remote-sensing data (Schwieder et al. 2022). For balance and mediator checks, we consider mowing events in 2017 to be representative of a non-drought year, thus avoiding reverse causality, i.e., in 2018, farmers may have reduced mowing in response to the drought. For overgrazing, we use a proxy indicator of grazing intensity at the parcel level based on livestock units in 2018 (Lange et al. 2022) since grazing data for Germany are unavailable. For grassland fertilization, we use the percentage of grassland fertilized in 2018 within each grid (Lange et al. 2022). An additional variable of interest is the European Green Belt area established in 2003 as an ecological network surrounding the former inner German border (Zmelik, Schindler and Wrbka 2011). We use a dummy variable identifying the network's grid cells within a 2.5 km buffer on both sides of the border (Noack et al. 2022).

In summary, the full set of controls *Z* in formulas (1) and (2) are: shares of the eight broad land cover categories; annual mean air temperature; total annual precipitation; percentage of clay and sand; mowing frequency in 2017; grazing intensity index; share of fertilized grassland; elevation; and ecological network. The next section validates our identification strategy.

TABLE 1 Summary statistics of the 20 variables used in the study.

Variable	Unit	Min	1st Quartile	Median	Mean	3rd Quartile	Max
NDFI mean	%	9.01	41.64	49.99	49.41	57.99	90.26
NDFI duration	No. days	11.90	120.45	136.62	141.81	157.02	229.00
LSIpc	/	0.00	0.24	0.31	0.30	0.37	0.69
Artificial land	%	0.00	0.00	0.03	0.00	0.02	0.73
Cropland	%	0.10	0.27	0.46	0.45	0.63	0.90
Woodland	%	0.00	0.08	0.23	0.17	0.34	0.80
Shrubland	%	0.00	0.00	0.00	0.00	0.00	0.11
Grassland	%	0.10	0.17	0.28	0.25	0.36	0.90
Bare land	%	0.00	0.00	0.00	0.00	0.00	0.37
Water and ice	%	0.00	0.00	0.01	0.00	0.00	0.71
Wetland	%	0.00	0.00	0.00	0.00	0.00	0.20
Mowing events 2018	No. events	0.02	0.84	1.13	1.09	1.38	4.50
Mowing events 2017	No. events	0.00	1.12	1.42	1.38	1.68	3.97
Fertilized grassland	%	0.00	0.09	0.23	0.28	0.43	1.00
Grazing intensity	/	0.00	0.83	1.01	1.00	1.17	3.00
Clay	%	1.77	9.65	17.24	18.82	23.37	39.61
Sand	%	0.01	25.25	45.57	37.85	70.13	93.70
Elevation	m	0.00	46.73	220.10	214.31	351.41	896.95
Average temperature	°C	6.95	10.00	10.28	10.36	10.70	11.58
Total precipitation	mm	231.23	415.26	480.04	474.21	532.30	1,078.60

5 | TESTS FOR IDENTIFICATION STRATEGY VALIDATION

Prior to validating our fuzzy RDD, we need to confirm 1) the exogeneity of the former inner German border, 2) the sharp discontinuity in the treatment, and 3) the continuity of potential confounding factors at the cut-off. Thus, we replace the outcome with different factors and check for discontinuities in a sharp RDD framework (Lee, Moretti and Butler 2004; Imbens and Lemieux 2008; Lee and Lemieux 2010), and formalize the regression model as:

$$Y_{is} = \alpha_1 + f\left(running_{is}, East_{is}\right) + \delta_1 East_{is} + \varphi_s + \varepsilon_{is}, \tag{5}$$

where Y_{is} is the factor under consideration for landscape i within border segment s, $f(running_{is}, East_{is})$ is a function of the running variable measuring the distance to the border, $East_{is}$ is an indicator variable defining whether landscape unit i is on the eastern side of the border, φ_s is a set of border segments' fixed effects, and ε_{is} is the error term. Function $f(running_{is}, East_{is})$ also allows to include different slopes on either side of the border by incorporating the polynomials of $running_{is}$, and the interactions between $East_{is}$ and the polynomials of $running_{is}$.

The identification assumption would be invalid if the former inner German border was established as a consequence of the environmental or topographic characteristics of the territory. By using the whole set of available observations in the 50 km buffer around the border, we conclude that the inner German border was a purely political construct with no topographic or environmental basis.[6] Table 2 reports that the sharp RDD model rejects the null hypothesis of discontinuities in the distribution of all environmental and topographic factors.

[6] Appendix J shows that results are robust to the exclusion of border fixed effects.

TABLE 2 Testing for spatial discontinuities in the distribution of environmental and topographic factors.

Environmental Factor	Coeff.	SE	P-value	Bandwidth	N West	N East
Precipitation	-7.493	5.982	0.210	18291	15754	13765
Temperature	0.060	0.038	0.116	17487	15154	13224
Clay	0.132	0.298	0.657	16373	14375	12562
Sand	-0.703	0.780	0.367	22158	18665	16469
Elevation	-9.824	7.057	0.164	17989	15579	13924

Notes: Sharp RDD with optimal bandwidth based on MSE; regression includes a cubic function of the running variable 'distance to the border' which is negative for western Germany and positive for eastern Germany; sample includes all grids in the 50 km buffer area.

The key feature of a fuzzy RDD is the presence of a sharp discontinuity of the treatment in the first stage. It is not required for the identification strategy to observe a sharp discontinuity in the outcome in the second stage because of the non-deterministic nature of the treatment condition discussed above. Figure 3 is an example of a sharp discontinuity in the first stage typical of a fuzzy RDD (Imbens and Lemieux 2008).

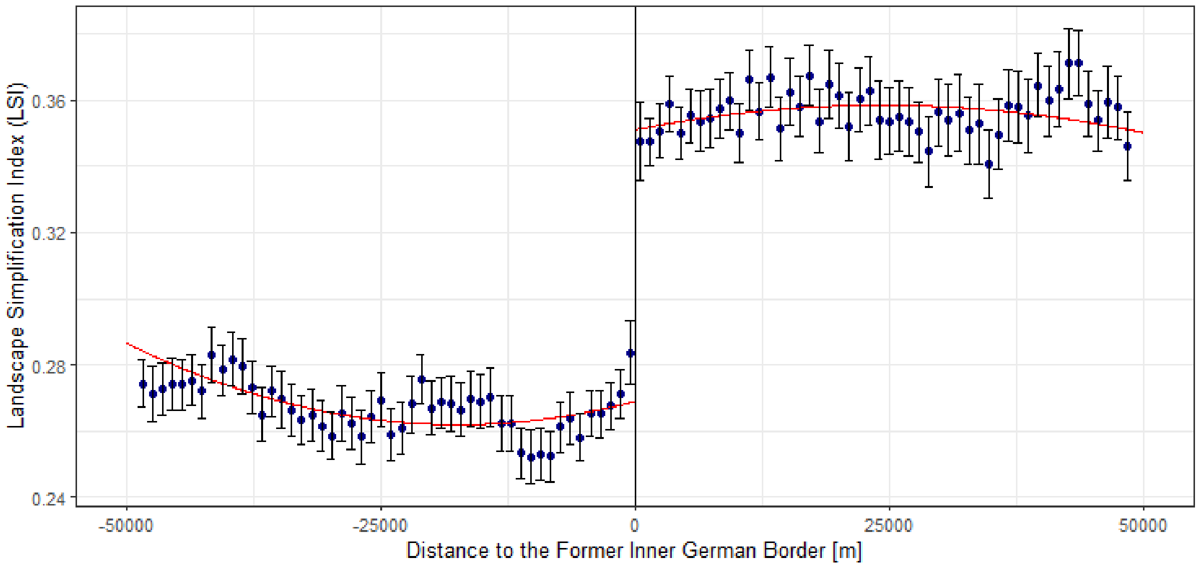

FIGURE 3 Discontinuity plots for the first stage of fuzzy RDD estimation.
Notes: Figure shows point estimates and 95 % confidence intervals for 1 km bins in the 50 km buffer around the former inner German border; functional form of the running variable 'distance to the border' is a quadratic polynomial and is negative for western Germany and positive for eastern Germany; treatment variable indicates a higher probability of landscape simplification on the eastern side of the border.

To confirm that all potential confounders are continuous at the cut-off, we use only the observations included in the analysis (presence of both grassland and cropland parcels) to plot the discontinuities in all potential confounders (Imbens and Lemieux 2008). Figures 4 and 5, which show no sharp discontinuities in the confounding factors, confirm that we can disentangle the effects of landscape simplification from other influencing factors.

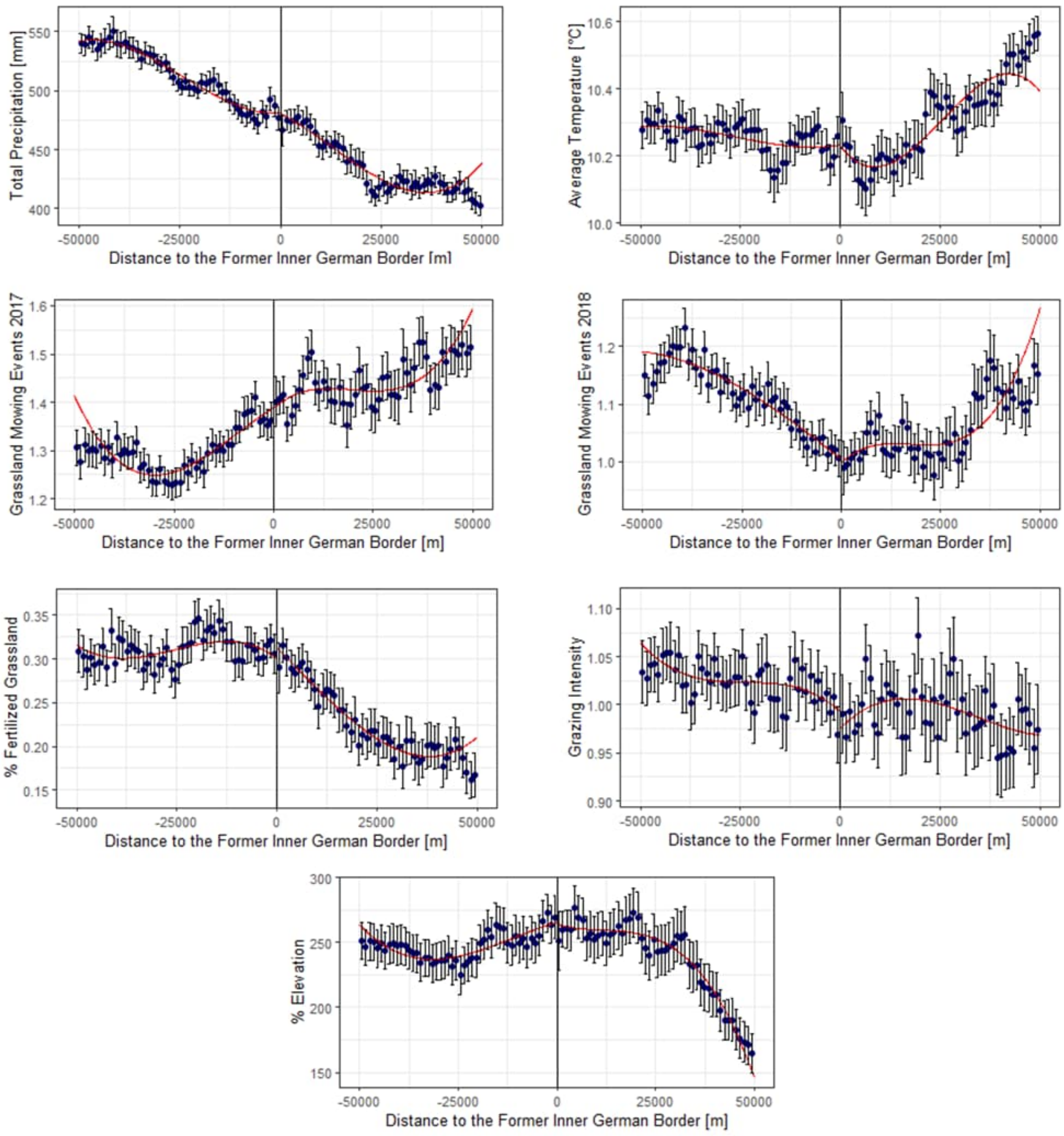

Figure 4 Continuity plots for potential influencing confounding factors.
Notes: Figure shows point estimates and 95 % confidence intervals for 1 km bins in the 50 km buffer around the former inner German border for potential confounders; functional form of the running variable 'distance to the border' is a cubic polynomial and is negative for western Germany and positive for eastern Germany.

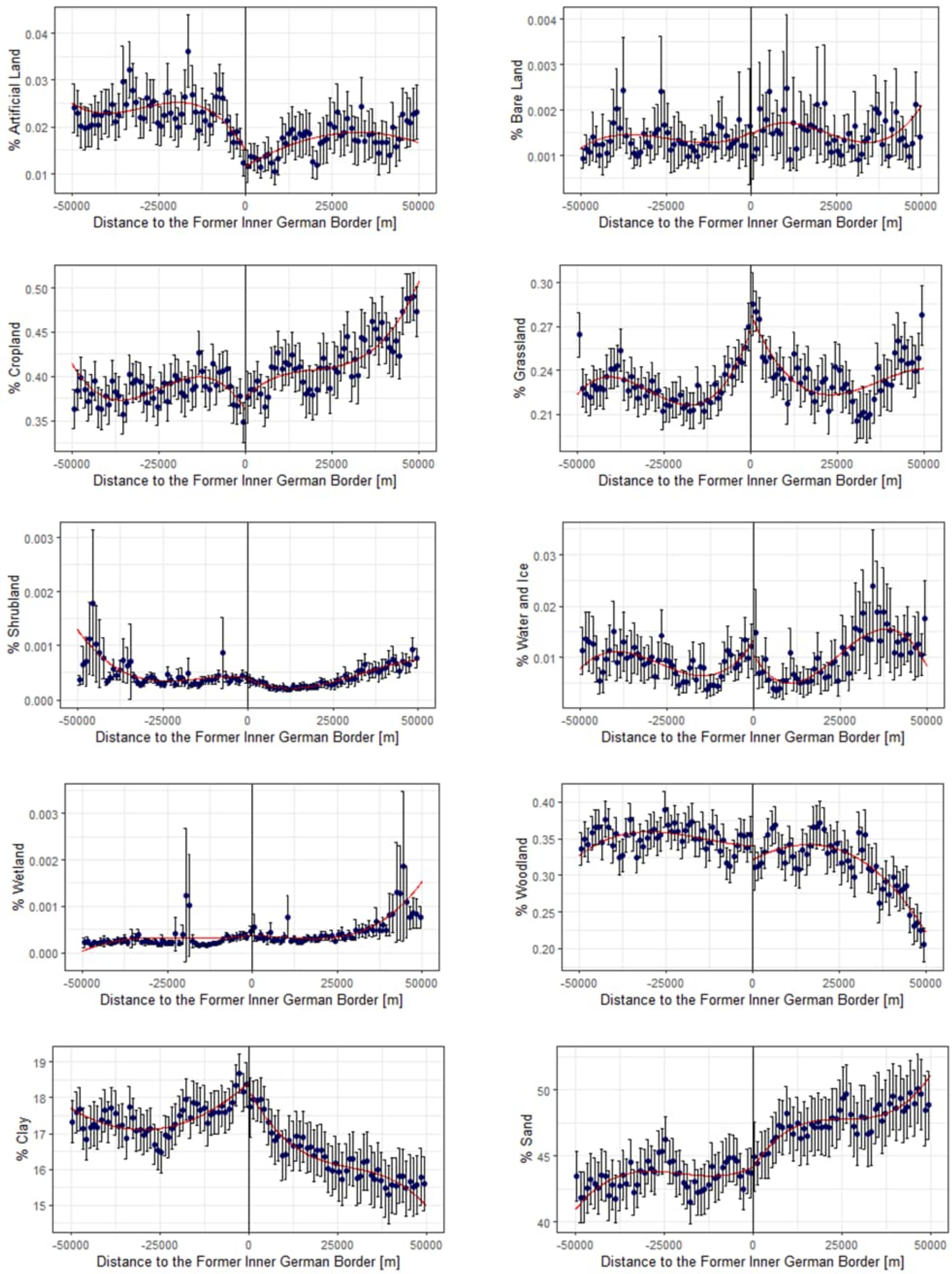

Figure 5 Continuity plots for potential influencing confounding factors.
Notes: Figure shows point estimates and 95 % confidence intervals for 1 km bins in the 50 km buffer around the former inner German border for potential confounders; functional form of the running variable 'distance to the border' is a cubic polynomial and is negative for western Germany and positive for eastern Germany.

6 | AGRICULTURAL LANDSCAPE SIMPLIFICATION AND GRASSLAND DROUGHT IMPACT

The baseline results suggest that an increase of 10 % in the LSI is associated with a 7 % increase in drought impact on grassland. Adding controls to our regression model, which does not substantially change the results, indicates that none of these factors play a dominant role in explaining drought impacts. Table 3 reports the results for the NDFI mean.

TABLE 3 Agricultural landscape simplification (LSI_{pc}) and grassland drought impact (NDFI mean).

Specification	First Stage	Second Stage (LATE)	N West	N East	Bandwidth
Baseline	0.061*** (0.006)	0.702*** (0.263)	5,288	4,775	12,572
+ Land cover	0.061*** (0.007)	0.761*** (0.262)	5,264	4,745	12,494
+ Bioclimate	0.061*** (0.007)	0.761*** (0.262)	5,264	4,745	12,494
+ Soil texture	0.061*** (0.007)	0.772*** (0.264)	5,240	4,731	12,447
+ Grassland use intensity	0.064*** (0.006)	0.742*** (0.252)	5,295	4,784	12,591
+ Elevation	0.059*** (0.006)	0.801*** (0.273)	5,102	4,583	12,055
+ Ecological networks	0.058*** (0.006)	0.828*** (0.283)	5,011	4,507	11,825

Notes: Treatment is a continuous index for landscape simplification (LSI_{pc}) both treatment and outcome are expressed in logarithms. For LSI_{pc} we add 1 before the log-transformation to ensure values are positive; first column reports the different model specifications; the regression includes a quadratic function of the running variable 'distance to the border' which is negative for western Germany and positive for eastern Germany. The baseline includes border segments' fixed effects. All specifications are additive and include further controls consecutively. 'Land cover' adds the landscape land cover shares (artificial land, cropland, woodland, shrubland, grassland, bare land, water/permanent snow/ice, and wetland). 'Bioclimate' adds the annual mean air temperature at 2 m above ground and the annual sum of monthly total precipitation. 'Soil texture' adds the percentage of clay and sand in the soil. 'Grassland use intensity' adds the number of mowing events detected by remote sensing products, a grazing intensity index based on livestock units, and the share of fertilized grassland. 'Elevation' adds landscape topographical characteristics and 'Ecological network' adds the dummy for the European Green Belt. The optimal bandwidth is calculated for each specification according to the MSE criterion and is equal on both sides of the boundary. Significance levels are 10 % (*), 5 % (**), and 1 % (***) based on p-values. Standard errors are reported in parentheses below the point estimates.

6.2 | Robustness checks

In employing the fuzzy RDD, a linear specification may result in an artificial discontinuity at the cut-off if the underlying relationship is non-linear, and conversely, using higher-order polynomials may lead to overfitting (Gelman and Imbens 2019). To avoid possible misleading distribution and artificial discontinuity we perform three operations: 1) Repeat the analysis introducing functional forms of the running variable ranging from linear to cubic polynomial (see Appendix E); 2) Implement a placebo test by shifting the actual former inner German border to the eastern and western sides and repeat the analysis (see Appendix F), i.e., if an observed discontinuity is no longer significant for all placebo cut-offs, the assumptions of our identification strategy hold at the original border; and 3) Run a manipulation test based on density discontinuity (Cattaneo, Jansson and Ma 2018) (see Appendix G), i.e., without systematic manipulation of the data, the frequency of our observations (grid cells with grassland) should remain continuous around the cut-off (McCrary 2008). We note that manipulation tests rejecting the null hypothesis of data manipulation validate our identification strategy.

To demonstrate model sensitivity to the bandwidth choice, we run supplementary regressions using the baseline specification and five additional bandwidth selections: 1) Two distinct MSE-optimal bandwidth selectors for below and above the cut-off point; 2) A single common MSE-optimal bandwidth selector for the sum of regression estimates; 3) Doubling the optimal bandwidth used in the main results; 4) Halving the optimal bandwidth; 5) Using all observations in the 50 km buffer. Table 4 shows the results.

TABLE 4 Regression results for different bandwidths.

BW Type	First Stage	Second Stage	BW West	BW East	N West	N East
Two different MSE-optimal bandwidth selectors below and above the cut-off	0.063*** (0.007)	0.740 *** (0.267)	5207	5007	13777	11807
One common MSE-optimal bandwidth selector for the sum of regression estimates	0.062*** (0.006)	0.753*** (0.250)	5789	5238	13896	13896
Halving the MSE-optimal bandwidth for the RD treatment effect estimator	0.033** (0.018)	1.284 (0.988)	2795	2564	6286	6286
Doubling the MSE-optimal bandwidth for the RD treatment effect estimator	0.061*** (0.005)	0.641*** (0.192)	9886	8366	25144	25144
Including all observations in the 50 km buffer	0.072*** (0.004)	0.157 (0.110)	19472	14968	50000	50000

Notes: Model specification includes border segments fixed effects and all controls; analogous to the main results, we use a fuzzy RDD with a quadratic function of the running variable 'distance to the border', which is negative for western Germany and positive for eastern Germany; significance levels are 10 % (*), 5 % (**), and 1 % (***) based on p-values; standard errors are in parentheses below point estimates.

Although the results substantiate the reliability of our main estimates for alternative decisions about the optimal bandwidth, they are not statistically significant when we halve the optimal bandwidth or include all observations in the dataset. We attribute this to insufficient statistical power of a smaller sample size in the first case and the inclusion of observations too far from the former inner German border in the second case.

Finally, we also use a different indicator for the landscape simplification treatment based on different rules for defining simplification (see Appendix H). The results show that the estimates are statistically significant and confirm the robustness of our approach.

7 | AGRICULTURAL LANDSCAPE SIMPLIFICATION AND FOREGONE REVENUES

We calculate the potential foregone revenues from increases in drought impact in two stages: 1) We use the biophysical growth model LINGRA-N (Wolf 2013; Qi, Murray and Richter 2017) to model the dry matter grassland yields, and 2) We calculate forgone revenues per ha of grassland fresh matter assuming that grasslands where the NDFI > 0 are no longer suitable for agricultural production.[7]

Following Schulz et al. (2024), we randomly sample 1000 grassland fields in the northern, center, and southern areas of the former inner German border where we identify the causal effect within the optimal bandwidth. We calculate different dry matter grassland yields per ha to account for topographic characteristics that may lead to differences in grassland productivity. For the model inputs, we use daily weather information, observed soil hydraulic properties, assumed nitrogen applications, and mowing dates from 2018 (see Appendix J). The model output shows a dry matter biomass yield productivity of 4 tons per ha (northern), 6 tons per ha (central), and 7 tons per ha (southern).[8] To calculate the average foregone revenues for each area, we use available average yield and price data for grassland fresh matter 2019–2023 (see Appendix K). The price of one ton of fresh matter, including 9 % VAT, is 115 €. Moreover, grassland fresh matter is on average 16 % heavier than dry matter, and approximately 7 % of fresh matter is lost during storage.

Given that a 10 % increase in landscape simplification in the eastern region leads to a 7 % increase in grassland drought impact, we estimate the corresponding dry matter biomass yield losses of 0.30 t/ha in the northern area, 0.44 t/ha in the central area, and 0.52 t/ha in the southern area. Converting these losses into grassland fresh matter and accounting for storage losses, the foregone revenues per ha are 37.22 € (northern), 54.59 € (central), and 64.51 € (southern).

[7] Data on price per ton of grassland dry matter are not available in official German statistics.
[8] Results are consistent with other publicly available data at the NUTS2 level (KTBL 2023).

Overall, the average foregone revenues per ha on the eastern side of the inner German border due to agricultural landscape simplification is 52.11 €.

8 | DISCUSSION AND CONCLUSIONS

Many factors characterize grasslands' susceptibility to drought, the landscape simplification is investigated in this paper. Compositional effects can influence above-ground biophysical interactions, and configuration effects can influence soil-plant interactions. Hydrological homogenization resulting from agricultural landscape simplification can influence the water cycle by altering water flow quantities and modifying water quality (Levia et al. 2020). Plant diversity in heterogeneous agricultural landscapes can enhance grassland functionality, for example, through species asynchrony (Hector et al. 2010), which is also effective under drought conditions (Haughey et al. 2018). The response of an ecosystem to droughts may also be influenced by the presence of different plant root architectures, which can be attributed to varying landscape configurations. Root architectures facilitate plant nutrient uptake, which in turn affects the ecosystem's resilience to drought conditions (Bao et al. 2014; Li, Zeng and Liao 2016). Finding that landscape configuration plays a more significant role than landscape composition in determining catchment hydrological flow variations, Liu et al. (2020), concluded that optimizing landscape configuration can enhance the regulatory capacity and efficacy of catchment water resources management. Moreover, enhancing landscape configurational heterogeneity in agricultural landscapes can also alleviate nitrate loads (Li et al. 2021).

In 2018, Germany experienced an exceptionally severe drought caused by a prolonged heatwave (Zscheischler and Fischer 2020). To understand how and why different landscape types vary in susceptibility to drought (Schmitt et al. 2022) we derived a novel remote-sensing product measuring the impact of droughts on grassland, used Germany’s former inner border as an exogenous predictor of an agricultural landscape simplification index, compiled a dataset of management practices, land cover, soil conditions, etc., and employed a spatially explicit fuzzy Regression Discontinuity Design (RDD). We found that a 10 % increase in agricultural landscape simplification increased drought impact by 7 % on the eastern sides of the border.

Droughts can also incur forgone revenues. It is possible that economic incentives, particularly those enabling landscape heterogeneity, can promote preventive landscape management policies. For the 2018 drought, we quantified the monetary losses per ha attributable to landscape simplification in terms of foregone revenues for the northern, central, and southern areas on the eastern part of the former inner German border as 37.22 €, 54.59 €, and 64.51 €, respectively. Given data availability, our calculation was based on grassland fresh matter prices and can thus be interpreted as a lower bound. Grassland productivity losses come at a higher cost for cattle farms, for instance, additional forage and concentrates including transportation costs occur to compensate, or in the worst case, even a reduction in livestock.

As with other studies employing fuzzy RDD, ours is not exempt from limitations. The estimated treatment effect is specific to compliers, which may restrict its generalizability. Moreover, the effect is context-dependent and may exhibit low external validity when applied to different settings. For instance, variations in plant functional trait composition across agricultural landscapes can result in differing levels of grassland susceptibility to drought, as compensation effects may vary.

Despite the limitations, our study offers policy implications. The European Union's Common Agricultural Policy (CAP), an important environmental policy instrument, aims to contribute to climate change adaptation through the implementation of efficient landscape management practices (European Union 2013). It emphasizes policies for maintaining grasslands in agricultural areas, e.g., the CAP 2023–2027 requires member states to ensure that the share of permanent grassland in the total agricultural area at the national, regional, and sub-regional levels does not drop below 5 % compared to 2018. Our research shows that enhancing agricultural landscape heterogeneity makes it possible to preserve grassland agroecosystems.

Interdisciplinary research provides opportunities to fulfill the CAP's aims. Extending the research in this paper could explore the different mechanisms through which agricultural landscape heterogeneity influences drought impacts, i.e., via changes in hydrological cycles and plant diversity. Our quantified productivity losses could give a first indication that financial incentives could exist for farmers to increase agricultural landscape heterogeneity. However, our calculation does not reflect cost savings from larger fields. There is a need to examine whether the decline in grassland yields in eastern Germany during moderate-to-severe droughts could be offset by the benefits in normal times by the economies of scale associated with larger fields. In 2013, farmlands in eastern Germany generated 50 % higher profits than in western Germany despite similar yield levels, due to the cost savings of larger machinery and reductions in labor requirements (Batáry et al. 2017).

Future climate projections for Europe indicate that the frequency and intensity of compound droughts and heatwaves will increase, that summer precipitation will decline, and more agricultural lands of all types will suffer drought effects (Domeisen et al. 2022). Europe needs policies that support effective adaptation strategies and rapid adjustments in landscape management practices as well as incentives that minimize losses.

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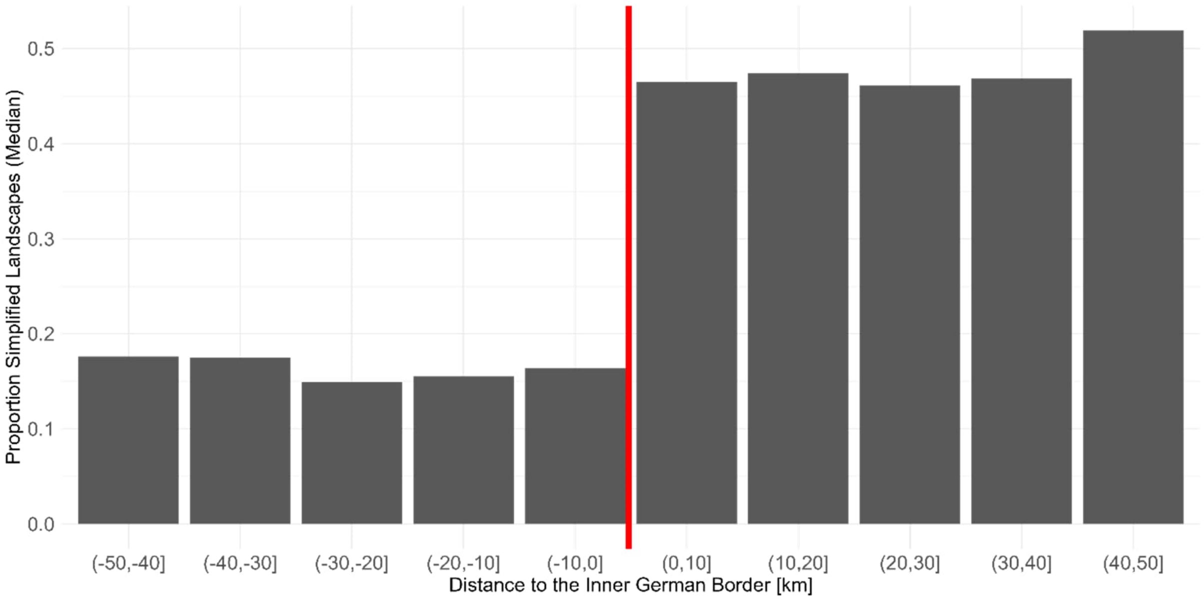
Supplementary Information to

The causal effect of agricultural landscape simplification on Germany's grasslands during a compound drought and heatwave in 2018

Contents

Appendix A: Probability of Observing Simplified Landscapes



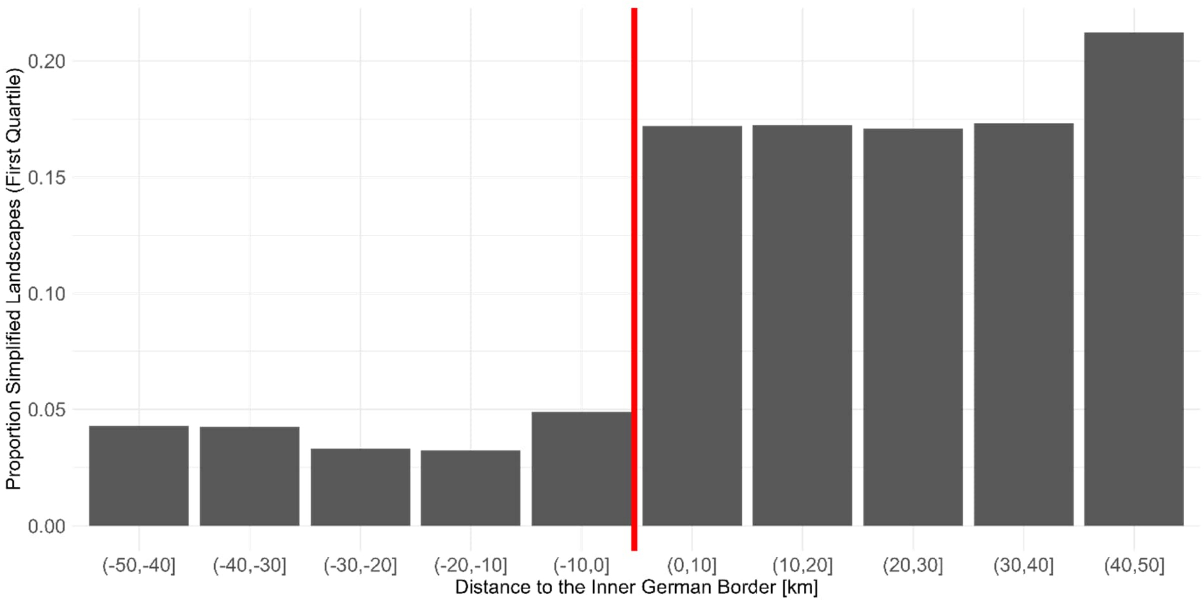


FIGURE A1 Probability of observing simplified landscapes on the eastern and western sides of the former inner German border.

Notes: The figures show the probability of a landscape having values for both ED and SHDI below the sample median (top figure) and below the first quartile (bottom figure) for 10 km bins in the 50 km buffer around the inner German border. To the right of the border is eastern Germany, which has a significantly high probability of having simplified landscapes.

Appendix B: Alternative Treatment

To assess the consistency of our primary treatment variable and the robustness of the model results to different definitions of the treatment variable, we construct an additional composite index based on alternative rules. Specifically, we develop a landscape simplification indicator that captures different levels of landscape simplification in terms of both compositional and configurational heterogeneity. Using the median of SHDI and ED within a 50km buffer, we establish thresholds below which a landscape is classified as simplified. We assign a value of 1 if the landscape falls below the median for both SHDI and ED (indicating higher levels of monoculture), and a value of 0 otherwise. The rule for defining this alternative treatment is formalized as follows:

$$LSI_{median,i} = \begin{cases} 1, & SHDI < 1.69 \; and \; ED < 179 \\ 0, & Otherwise \end{cases} \quad (1)$$

Appendix H displays the results of model estimates using LSI_{median} as the treatment variable.

Appendix C: Land Cover Dataset

To construct the landscape simplification index (LSI), we use data on the spatial distribution of 24 crop and land use types at the parcel level from Blickensdörfer et al. (2022):

1. Grassland
2. Winter wheat
3. Winter rye
4. Winter barley
5. Other winter cereal
6. Spring barley
7. Spring oat
8. Other spring cereals
9. Rapeseed
10. Silage maize
11. Grain maize
12. Potato
13. Sugar beet
14. Legume
15. Sunflower
16. Strawberry
17. Asparagus
18. Onion
19. Carrot
20. Other vegetables
21. Hops
22. Vineyard
23. Orchard
24. Small woody features

Appendix D: Estimates of NDFI Duration

TABLE A1 The impact of agricultural landscape simplification (LSI_{pc}) on grassland drought duration (NDFI duration).

Specification	First Stage	Second Stage	N West	N East	Bandwidth
		NDFI Duration			
Baseline	0.061*** (0.007)	0.244 (0.244)	5,367	4,839	12,731
+ Land cover	0.061*** (0.007)	0.265 (0.242)	5,390	4,864	12,786
+ Bioclimate	0.061*** (0.007)	0.265 (0.242)	5,390	4,864	12,786
+ Soil texture	0.061*** (0.006)	0.266 (0.241)	5,425	4,895	12,866
+ Grassland use intensity	0.064*** (0.006)	0.262 (0.230)	5,511	4,994	13,147
+ Elevation	0.059*** (0.006)	0.327 (0.255)	5,192	4,682	12,309
+ Ecological networks	0.058*** (0.006)	0.387 (0.265)	5,060	4,540	11,935

Appendix E: Sensitivity to Polynomial Function

TABLE A2 Testing for the sensitivity of the main results (NDFI Mean and LSI_{pc}) to changes in the polynomial function of the running variable.

Specification	First Stage	Second Stage	N West	N East	Bandwidth
LOCAL LINEAR REGRESSION					
Baseline	0.060*** (0.006)	0.611** (0.246)	2,803	2,569	6,303
+Land Cover	0.060*** (0.006)	0.667*** (0.248)	2,781	2,543	6,247
+Bioclimate	0.060*** (0.006)	0.667*** (0.248)	2,781	2,543	6,247
+Soil Texture	0.060*** (0.006)	0.670*** (0.248)	2,775	2,538	6,238
+Grassland Use Intensity	0.063*** (0.006)	0.645*** (0.237)	2,852	2,608	6,425
+Elevation	0.057*** (0.006)	0.739*** (0.261)	2,700	2,456	6,028
+Ecological Network	0.056*** (0.006)	0.778*** (0.266)	2,681	2,441	5,974
LOCAL CUBIC REGRESSION					
Baseline	0.060*** (0.007)	0.813*** (0.311)	7,542	6,716	18,874
+Land Cover	0.060*** (0.007)	0.870*** (0.311)	7,522	6,694	18,799
+Bioclimate	0.060*** (0.007)	0.870*** (0.311)	7,522	6,694	18,799
+Soil Texture	0.060*** (0.007)	0.887*** (0.31)	7,555	6,722	18,901
+Grassland Use Intensity	0.062*** (0.007)	0.854*** (0.292)	7,681	6,808	19,232
+Elevation	0.057*** (0.007)	0.935*** (0.340)	7,105	6,378	17,664
+Ecological Network	0.056*** (0.007)	0.984*** (0.351)	6,993	6,289	17,350

Notes: The main analysis is repeated using a local linear and local cubic regression instead of a local quadratic regression for the function of the running variable. The running variable 'distance to the border' is negative for western Germany and positive for eastern Germany. The optimal bandwidth is calculated for each specification according to the MSE criterion and is equal on both sides of the boundary. Significance levels are 10 % (*), 5 % (**), and 1 % (***) based on p-values. Standard errors are reported in parentheses.

Appendix F: Test with Placebo Borders

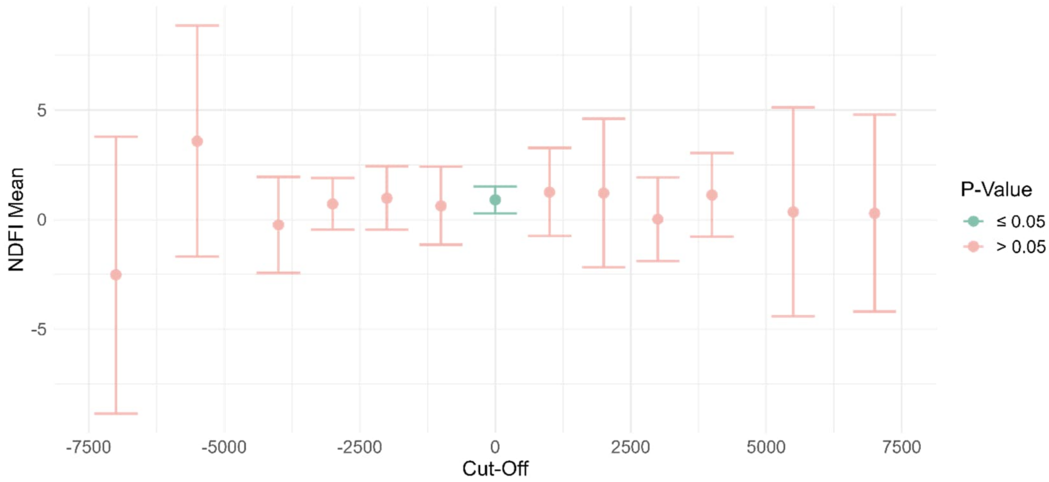


FIGURE A4 Placebo borders plot for NDFI mean.
Notes: We moved the RDD cut-off from the actual former inner German border toward East and the West. The estimate should converge towards zero as the RDD cut-off is moved further from the actual former inner German border. The horizontal axis depicts the distance of the regression discontinuity cut-off to the border in meters. Negative values indicate an RDD cut-off to the western of the former inner German border, positive values indicate an RDD cut-off to the eastern of the former inner German border. The color displays the significance levels and bars confidence intervals at 5 %.

Appendix G: Manipulation Test

TABLE A4 Manipulation testing procedure using the local polynomial density estimators proposed in Cattaneo, Jansson and Ma (2018).

Window Length Each Side	N West	N East	P-value
1307.242	645	613	0.3821
1960.864	1185	1143	0.3955
2614.485	1652	1633	0.7535
3268.106	2116	2108	0.9142
3921.727	2584	2557	0.7169
4575.348	3015	2983	0.6890
5228.969	3467	3405	0.4618
5882.591	3906	3817	0.3167
6536.212	4314	4209	0.2599

Notes: The RDD manipulation test procedures proposed by Cattaneo, Jansson, and Ma (2018) involve the use of local polynomial density estimators to detect manipulation of the running variable in RDD. The procedure begins by estimating the density of the current variable separately on each side of the cutoff point. This is done using local polynomial regressions, which are flexible and can capture non-linearities in the data. The method involves selecting an optimal bandwidth to localize the estimation around the cutoff. The null hypothesis tested is that there is no discontinuity in the density at the cutoff, implying no manipulation. A significant discontinuity in the density at the cutoff suggests possible manipulation around the cutoff. The method provides robust statistical inference by constructing valid confidence intervals and p-values using robust bias correction techniques. Moreover, it ensure that results are reliable even in finite samples, avoiding the pitfalls of traditional density estimation methods. The first column shows the width of the window used for the test, the second and third columns show the number of observations on each side of the boundary, and the last column shows the p-value. The results suggest that we cannot reject the null hypothesis of no discontinuity for all selected windows.

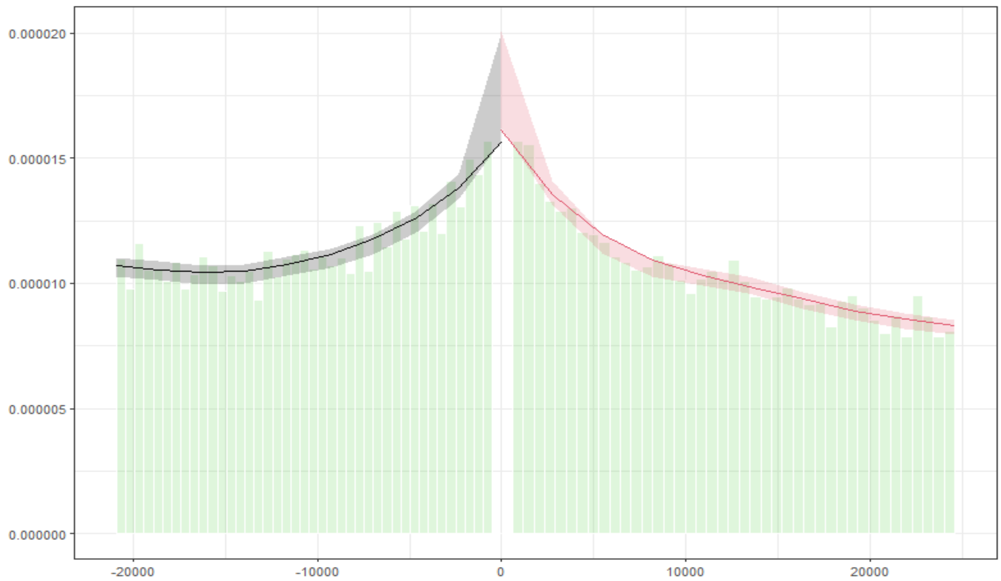


FIGURE A2 Density plot of the running variable around the cutoff point using local polynomial estimators.
Notes: The plot shows the estimated density on both sides of the cutoff, with confidence intervals shaded. A significant jump or discontinuity at the cutoff could indicate possible manipulation of the forcing variable. On the x-axis are the values of the running (forcing) variable ‘distance to the border’, and on the y-axis is the estimated density of the running variable, which indicates how often values of the driving variable occur around the cutoff.

Appendix H: Estimates of Alternative Treatment

TABLE A3 The impact of agricultural landscape simplification alternative treatment (LSI_{median}) on grassland drought impact (NDFI Mean).

Specification	First Stage	Second Stage	N West	N East	Bandwidth
		NDFI Mean (%)			
Baseline	0.270*** (0.038)	7.151** (3.317)	4,698	4,218	11,009
+Land Cover	0.273*** (0.037)	7.729** (3.272)	4,730	4,243	11,085
+Bioclimate	0.273*** (0.037)	7.729** (3.272)	4,730	4,243	11,085
+Soil Texture	0.274*** (0.037)	7.787** (3.256)	4,746	4,263	11,131
+Grassland Use Intensity	0.272*** (0.037)	7.858** (3.280)	4,750	4,267	11,148
+Elevation	0.247*** (0.038)	8.707** (3.698)	4,522	4,062	10,548
+Ecological Network	0.246*** (0.038)	9.086** (3.738)	4,505	4,051	10,514

Notes: The treatment is a binary indicator for landscape simplification (LSI_{median}), which considers simplified a landscape with composition and configuration metrics below the sample median. The running variable ‘distance to the border’ is negative for western Germany and positive for eastern Germany. The optimal bandwidth is calculated for each specification according to the MSE criterion and is equal on both sides of the boundary. Significance levels are 10 % (*), 5 % (**), and 1 % (***) based on p-values. Standard errors are reported in parentheses below the point estimates.

Appendix I: Robustness of Environmental and Topographical Factors

TABLE A4 Testing the robustness of spatial discontinuities in the distribution of environmental and topographical factors by excluding fixed effects from the regression model.

Environmental Factor	Coeff.	SE	P-value	Bandwidth	N West	N East
Precipitation	-9.960	7.260	0.170	18427	15856	13880
Temperature	0.071	0.045	0.112	17883	15464	13510
Clay	0.178	0.338	0.599	25136	20878	18443
Sand	-0.087	1.290	0.946	18888	16225	14292
Elevation	-15.610	11.298	0.167	19189	16471	14758

Notes: The framework is a sharp RDD with optimal bandwidth based on MSE. The regression includes a cubic function of the running variable ‘distance to the border’ which is negative for western Germany and positive for eastern Germany. In contrast to the main analysis, the sample includes all grids in the 50 km buffer area.

Appendix J: Biophysical Model Set-Up

We used the biophysical growth model LINGRA-N, developed to simulate grass yields across the European Union and implemented as an R package (Qi, Murray and Richter 2017; Qi et al. 2018). The model requires daily weather data, soil hydraulic properties, nitrogen application rates, and mowing dates as inputs and produces outputs including grassland dry matter biomass. Several data sources were used to provide the necessary inputs. Daily weather data - including minimum and maximum temperatures, precipitation, wind speed, vapor pressure and radiation - were obtained from the nearest available weather station (DWD 2022a; DWD 2022b). Soil depth data were obtained from Pelletier et al. (2016), while soil hydraulic properties were obtained from Panagos et al. (2022). Estimated mowing dates were provided by the authors of the mowing frequency dataset on request (Schwieder et al. 2022). Following Schulz et al. (2024), for the first nitrogen fertilization date we calculated the day when the cumulative sum of positive mean daily temperatures reached 200, using weighting adjustments: temperatures in January were multiplied by 0.5, in February by 0.75 and from March onwards by 1, with negative temperatures set to zero. Subsequent fertilization was assumed to take place ten days after each harvest. Nitrogen application rates followed the maximum rates for grassland as specified in the Nitrate Directive (BGBl 2017) and were spread proportionally over all fertilization events.

Appendix K: Grassland Yields and Price Data

TABLE A5 Average grassland yields and prices of fresh grassland matter for Germany in the period 2019-2023

Variable/ Number Mowing Events	**1**	**2**	**3**	**4**	**5**
Grassland Dry Matter Including Storage (t/ha)	3.15	4.34	6.29	6.29	7.14
Grassland Fresh Matter Including Storage (t/ha)	3.66	5.05	7.31	7.31	8.3
Ratio Grassland Fresh Matter/Dry Mater	1.16	1.16	1.16	1.16	1.16
Grassland Fresh Matter Excluding Storage Losses (t/ha)	3.41	4.70	6.80	6.80	7.72
Ratio Grassland Fresh Matter / Fresh Matter Excluding Storage Losses	1.07	1.07	1.07	1.07	1.07
Price Grassland Fresh Matter (€/t)			115		

Notes: We use average data for 2019-2023 published by the Bavarian State Institute for Agriculture. Data can be found (in German) at: https://www.stmelf.bayern.de/idb/bodenheu.html.

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