Wildlife Management Areas, Deer Quality, and Rural Land Values:
A Spatial Hedonic Analysis of Arkansas

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Abstract

This paper develops and validates a spatial hedonic pipeline for estimating the proximity, trophy-quality, and wildlife-disease effects of public hunting lands on rural land values in Arkansas. Because parcel-level transaction data is not yet publicly available, we use 308,220 tax-assessed agricultural parcels as a proof-of-concept source, matched to seventeen spatial control variables spanning soil quality, hydrology, land cover, roads, urban access, federal public lands, gas wells, Conservation Reserve Program (CRP) enrollment, elevation, deer-management zones, Chronic Wasting Disease (CWD) zones, and Arkansas Game and Fish Commission (AGFC) harvest biodata. We demonstrate the pipeline's econometric properties through nine identification-robustness perturbations: functional-form checks (IHS), spatial inference (Conley HAC across multiple bandwidths; wild cluster bootstrap), generated-regressor bootstrap for the deer-quality z-score, soil-control attenuation, CWD-intensity sensitivity, donut-hole exclusion, leave-one-out county sensitivity, coarsened exact matching, and placebo-distance tests across thirty random-point configurations. The WMA $< 1/4$ mile coefficient is stable at approximately -0.19 across all perturbations, and the placebo distribution confirms that the effect is specific to actual WMA locations ($p < 0.001$). The assessed-value gradient is negative—opposite the positive-amenity prediction for transaction prices—reflecting WMA placement on marginal terrain and assessor under-reaction to recreation amenities. The validated pipeline is designed to detect the theoretically predicted positive gradient in sale data once acquired, positioning a staggered

difference-in-differences design around Arkansas's phased CWD-zone expansion (2016, 2018, 2021) as the natural follow-on analysis.

1 Introduction

Arkansas ranks among the premier deer hunting destinations in the United States, with the white-tailed deer harvest consistently exceeding 150,000 animals per year and the hunting economy contributing an estimated $1.5 billion annually to the state economy [U.S. Fish and Wildlife Service, 2016]. Hunting lease markets, outfitter operations, and recreational land purchases represent a growing share of rural land demand, particularly in regions where traditional agricultural returns are declining. Yet despite the economic significance of hunting to rural land markets, remarkably little hedonic evidence exists on how proximity to public hunting lands—specifically state-managed Wildlife Management Areas (WMAs)—capitalizes into property values.

The hedonic pricing framework of Rosen [1974] predicts that if hunters value access to quality hunting, proximity to well-managed public hunting lands should be reflected as a premium in surrounding rural property values—the positive amenity capitalization documented for open space, water bodies, and protected areas across the environmental economics literature [Cho et al., 2006, Lansford and Jones, 1995, Walls et al., 2015, Bastian et al., 2002]. In agricultural land markets, Palmquist [1989] shows that hedonic gradients on spatial attributes can be interpreted as the equilibrium valuation of those attributes for both productive and consumptive (recreational) uses. Under this theoretical prior, the coefficient on WMA proximity in a hedonic regression of rural land transaction prices should be *positive*: closer equals more valuable.

The empirical obstacle is data. Arkansas does not publicly release parcel-level transaction records, and the commercial alternative—CoreLogic's Zillow Transaction and Assessor Database (ZTRAX)—requires institutional licensing still pending for this project. We therefore build and validate the spatial hedonic pipeline on the one parcel-level dataset that is universally available: tax-assessed agricultural values from the Arkansas GIS Office's Computer-Assisted Mass Appraisal (CAMA) snapshot, covering 308,220 vacant-agricultural (AV-classified) parcels matched to seventeen spatial control variables (soil quality, hydrology, land cover, roads, urban access, federal public lands, gas wells, CRP enrollment, elevation, deer-management zones, CWD zones, and AGFC harvest biodata). Assessed values are an imperfect proxy for market prices—distorted by the 20% statutory assessment ratio, infrequent reappraisals, and assessor smoothing—but they share the same parcel-level spatial structure that transaction prices will, making them a defensible proof-of-concept source for stress-testing the econometric pipeline before a full causal analysis.

This paper's contribution is methodological. We construct a spatial hedonic pipeline for Arkansas rural land values, demonstrate its econometric properties through nine identification-robustness checks (functional form, spatial inference, generated-regressor bias, soil-control attenuation, CWD intensity, donut-hole exclusion, leave-one-out county, coarsened exact matching, and placebo distance), and show that the WMA $< 1/4$ mile coefficient is stable across all perturbations. The assessed-value cross-section produces a *negative* gradient—opposite the positive amenity prediction—which we attribute primarily to WMA placement on marginal terrain (bottomland hardwoods, steep Ozark hillsides, flood-prone land) combined with assessor under-reaction to recreation amenity value. This sign discrepancy is itself diagnostic: it motivates transaction-data acquisition by showing that assessed values cannot substitute for sale prices when testing amenity capitalization. The validated pipeline is designed to detect the theoretically predicted positive gradient as soon as rural sale data become available, with a staggered difference-in-differences design around Arkansas's phased CWD-zone expansion (10 counties in 2016, 15 in 2018, 17 in 2021) as the leading follow-on identification strategy [Callaway and Sant'Anna, 2021, Sun and Abraham, 2021].

The integration of deer-harvest biological data into a hedonic land-value model is, to our knowledge, novel. Age-normalized Boone & Crockett z-scores constructed from AGFC check-station records serve as a continuous measure of spatial variation in deer trophy quality that can be tested as a hedonic attribute. No prior study has used administrative wildlife harvest records as a deer quality index in a property value regression. Section 5 reports the main regression results. Section 6 presents the nine identification-robustness checks. Section 7 presents the deer-quality deep dive. Section 8 discusses interpretation, particularly the assessed-value-vs.-sale-price divergence. Section 9 summarizes limitations and the transaction-data roadmap.

2 Literature Review

2.1 Hedonic Amenity Capitalization and Public-Land Proximity

The theoretical foundation is the hedonic pricing model of Rosen [1974], which decomposes differentiated-good prices into the implicit values of their attributes, with microeconomic roots in Lancaster [1966]. Palmquist [1989] extends the framework to treat land as a differentiated factor of production, showing that hedonic coefficients on land attributes can be interpreted as marginal productivities in agricultural markets where parcels serve both productive and consumptive (recreational) functions. Applied to rural land, the hedonic equation accommodates spatial characteristics as continuous or binned distance gradients, whose functional form—linear, log-linear, or nonparametric—must be empirically determined; we estimate both continuous and binned specifications.

A substantial literature documents positive capitalization of environmental amenities. Cho et al. [2006] find that forest and open-space proximity raises farmland values with distance decay; Lansford and Jones [1995] document water-body premia within one to two miles; Walls et al. [2015] estimate positive effects of protected-area proximity on residential values. For agricultural markets specifically, Bastian et al. [2002] show that wildlife habitat and scenic amenities capitalize into Wyoming agricultural values even where production is the dominant use, and Abbott and Klaiber [2010] demonstrate that the value of open-space preservation depends on the alternative land use it displaces.

Hedonic evidence on public hunting land is scarcer. The only parcel-level comparison is Casola et al. [2022], who estimate spatially heterogeneous effects of North Carolina Game Lands on residential sale prices: proximity is positive at moderate distances but adjacency is negative, consistent with congestion or nuisance-wildlife effects. Their study uses residential properties, omits harvest-quality variables, and does not consider CWD. On the income side, Hussain et al. [2013] estimate that hunting-lease income capitalizes at a 7.55% rate in Mississippi forestland sales (\$1/acre lease ≈ \$13.25/acre in sale price), and Munn and Hussain [2010] find that a 10% increase in trophy-deer share raises lease rates by roughly \$106 per hunter on Mississippi 16th Section lands. Pope and Goodwin [1984] estimates that hunting rights broadly add 10–25% to farmland values using farm-level survey data. None of these papers jointly estimates WMA proximity, harvest quality, and CWD effects—the methodological gap this pipeline addresses.

Identification is the common challenge. Public-hunting lands are not randomly placed: agencies establish WMAs on marginal terrain (bottomland, steep slopes, flood-prone areas), creating mechanical negative correlation between WMA proximity and agricultural value. Walls et al. [2015] address this with boundary discontinuity designs; we rely on county and deer-zone fixed effects to absorb area-level confounders and complement with nine identification-robustness checks (Section 6), while acknowledging that cross-sectional identification remains limited until transaction data enable difference-in-differences designs.

2.2 Wildlife Disease Economics and Arkansas Context

Chronic Wasting Disease (CWD), a fatal prion disease of cervids, has emerged as a significant wildlife-management concern since its expansion beyond endemic areas in the early 2000s. Bishop [2004] and Zimmer et al. [2012] document declines in hunting participation (5–10%) and license revenue in affected areas, with larger effects on non-resident hunters. Gavin et al. [2019] estimate a 5.4% decline in Wisconsin license demand after CWD detection, representing \$96 million in consumer-surplus loss over 2002–2015, with effects attenuating as hunters habituated. Tanger et al. [2025] provide the first peer-reviewed hedonic estimate of CWD capitalization into land markets, finding that on-property CWD detection reduces Tennessee and Mississippi hunting-lease rates by 22% ($1.84/acre/year) with no significant effect for nearby-property detection. No study has yet estimated CWD effects on sale prices—a gap that requires transaction data, temporal variation in CWD status, and a credible control group.

Arkansas provides both the setting and the identifying variation. The state's diverse physiographic regions—the flat, productive Mississippi Delta; the rugged Ozark Plateau; the Ouachita Mountains—generate substantial heterogeneity in agricultural land value and hunting quality, with WMA placement patterns that reflect this geography: Delta WMAs (Bayou Meto, Dagmar, Rex Hancock–Black Swamp) manage waterfowl and deer in bottomland hardwoods, while Ozark WMAs (Gene Rush, Piney Creeks, Wedington) occupy steep forested terrain. The Arkansas CWD timeline—initial detection in Newton County in February 2016, phased zone expansion to 15 counties in 2018 and 17 in 2021—supplies the staggered treatment assignment needed for the Callaway and Sant'Anna [2021] or Sun and Abraham [2021] difference-in-differences estimators, once transaction data become available.

3 Study Area and Data

3.1 Study Area and Sample

The study area covers all 75 Arkansas counties (approximately 53,000 square miles), encompassing 191 WMA boundaries managed by the AGFC, the 17 CWD management-zone counties as of 2024–25, and the state's 20 deer management zones organized into six Deer Management Units (DMUs). Figure 1 displays the WMA, CWD, and deer-zone boundaries. The nested DMU–zone–county structure provides natural fixed-effect groups for absorbing zone-level variation in hunting regulation and habitat quality.

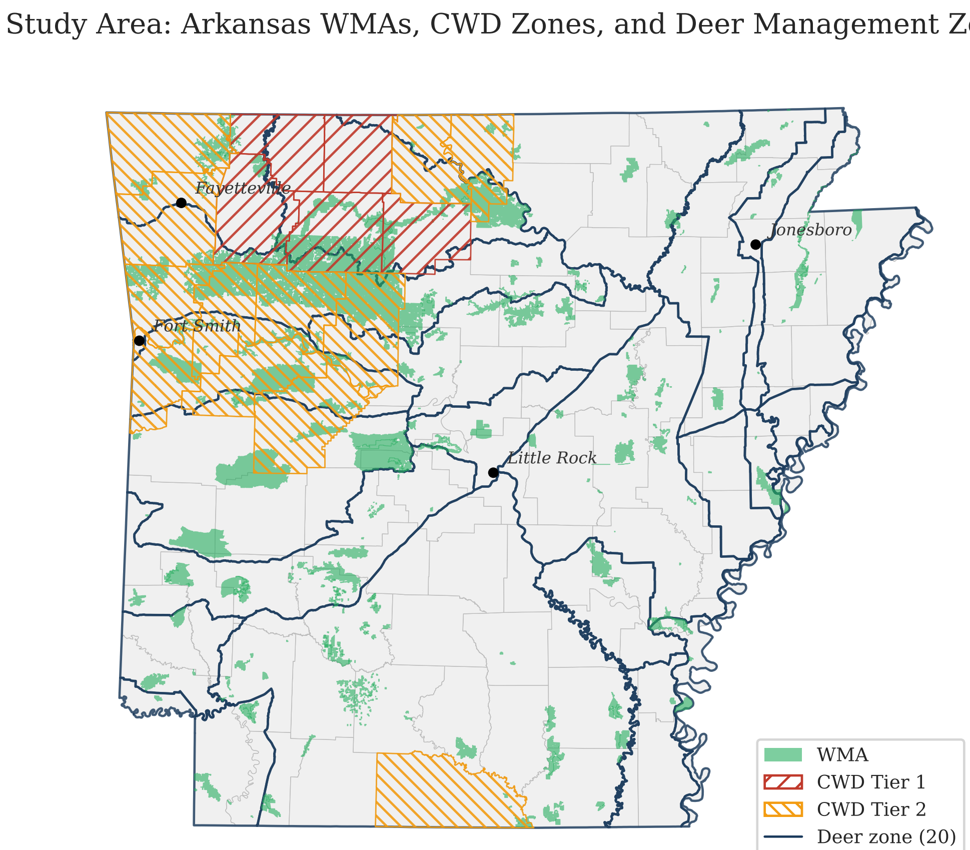

Figure 1: Study area map: Wildlife Management Areas (WMAs, green), CWD management-zone boundaries (Tier 1 red hatched, Tier 2 orange hatched), and the 20 deer management zones (dark blue outlines) across Arkansas's 75 counties.

The spatial backbone is 2,111,591 parcel centroids from the Arkansas GIS Office (PARCEL_CENTROID_CAMP, September 2025 snapshot) with CAMA attributes (assessed land value, acreage, parcel type, county). The statewide data is distributed as point centroids rather than polygon boundaries; all distance computations therefore measure from the centroid to the nearest WMA boundary edge. For large parcels near WMA boundaries, centroid distance may overstate the true nearest-edge distance. The *boundary_adjacent_wma* control (Section 4.2) partially addresses this by flagging parcels whose polygon boundary touches a WMA, and the donut-hole robustness test (Section 6) confirms the gradient survives after dropping the highest-leverage near-boundary parcels. The analysis sample restricts to 308,220 vacant-agricultural (AV) parcels between 5 and 5,000 acres, trimmed at the 1st and 99th percentiles of land value per acre ($86/ac and $1,250/ac). The 5-acre minimum excludes 42,900 sub-agricultural-scale parcels (residential lots, garden plots, assessment artifacts); the 5,000-acre cap is non-binding (zero AV parcels exceed it). Section 6 reports a sample-filter sensitivity test confirming that the WMA proximity gradient is unchanged across alternative acreage minimums (1, 5, 10 acres) and trim thresholds (none, 1/99, 2.5/97.5, 5/95). Vacant-agricultural is the cleanest dependent variable for proximity-gradient estimation: parcels with agricultural improvements (AI, AM types) conflate land value with structure value in the CAMA assessed total. The dependent variable is the natural log of assessed land value per acre; Figure 2 maps county-mean values. Summary statistics are in Table 1; the full variable dictionary and data-acquisition pipeline are in Appendix B.

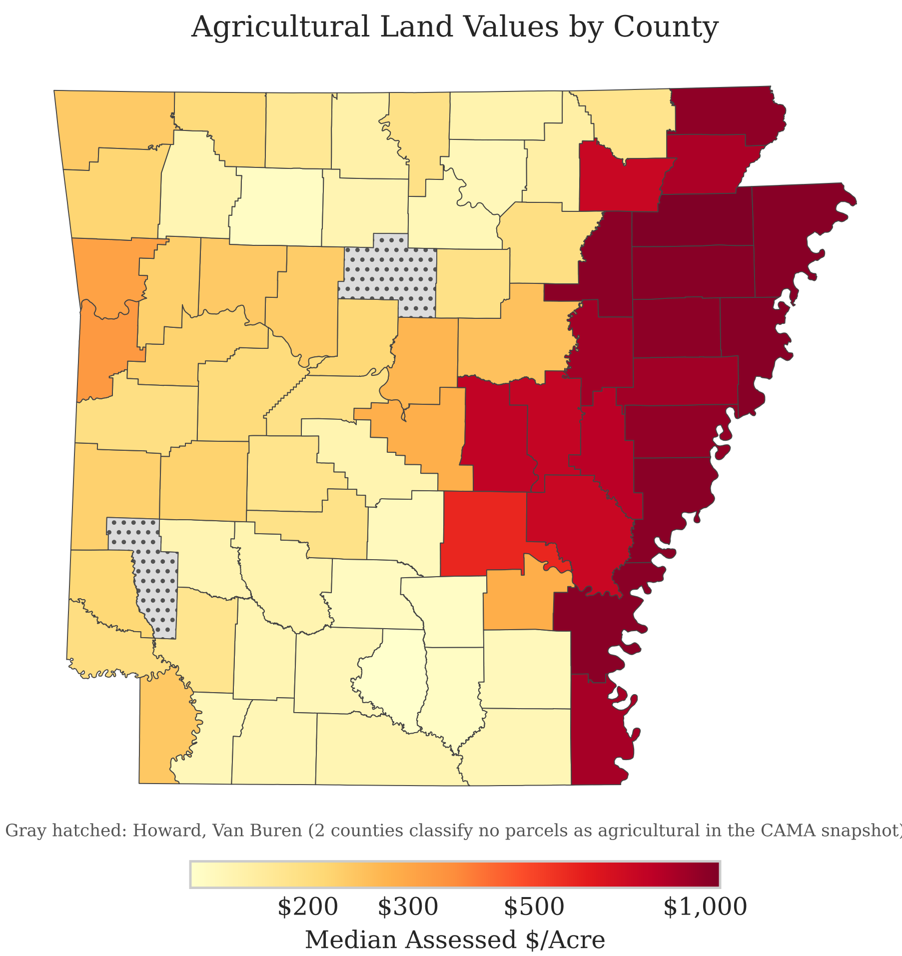

Figure 2: Mean assessed land value per acre by county. Higher values (darker shading) concentrate in the Delta agricultural region and near metropolitan Northwest Arkansas and Pulaski counties.

Table 1: Summary Statistics (N = 308,220 AV-only parcels)

Variable	Mean	SD	Min	Max
Dependent variable and parcel-level attributes (N = 308,220 parcels)				
Assessed land value/acre ($)	832	1,204	4	12,500
ln(land value/acre)	5.94	1.27	1.39	9.43
Distance to WMA (km)	8.12	7.95	0.00	49.8
Parcel acreage	94.7	186.3	5.0	5,000
nccpi_weighted_avg (parcel)	0.47	0.20	0.01	0.98
is_forest	0.15	0.36	0	1
is_wetland	0.03	0.18	0	1
in_100yr_floodplain	0.08	0.27	0	1
in_national_forest	0.02	0.14	0	1
is_prime_farmland (SSURGO)	0.28	0.45	0	1
in_fayetteville_shale	0.11	0.31	0	1
Elevation (km)	0.15	0.12	0.02	0.77
ln(dist. paved road, km)	−0.82	1.14	−4.61	3.91
ln(dist. urban area, km)	2.89	0.98	−2.30	4.79
ln(dist. water body, km)	−0.41	1.22	−6.91	3.47
Zone-level attribute (20 zones, repeated per parcel)				
mean_bc_zscore (zone-level)	0.024	0.22	−0.23	0.73
County-level attributes (73 counties, repeated per parcel; used in Model 5)				
crp_pct_county_area (%)	0.56	0.81	0.00	3.77
in_cwd_zone (FY25)	0.24	0.43	0	1
ln(total population)	10.11	0.97	8.46	12.90
ln(median household income)	10.87	0.18	10.45	11.45

Figure 3 displays the dependent-variable distribution before and after the 1st/99th percentile trim. The distribution is bimodal, reflecting the Delta/Ozark physiographic split in Arkansas agricultural land values: a lower mode near ln(value/ac) ≈ 4.5 (marginal Ozark and Ouachita land) and a higher mode near ln(value/ac) ≈ 7.0 (productive Delta row-crop ground). The trim cuts remove roughly 2% of AV parcels concentrated at both extremes of the raw assessed-value distribution.

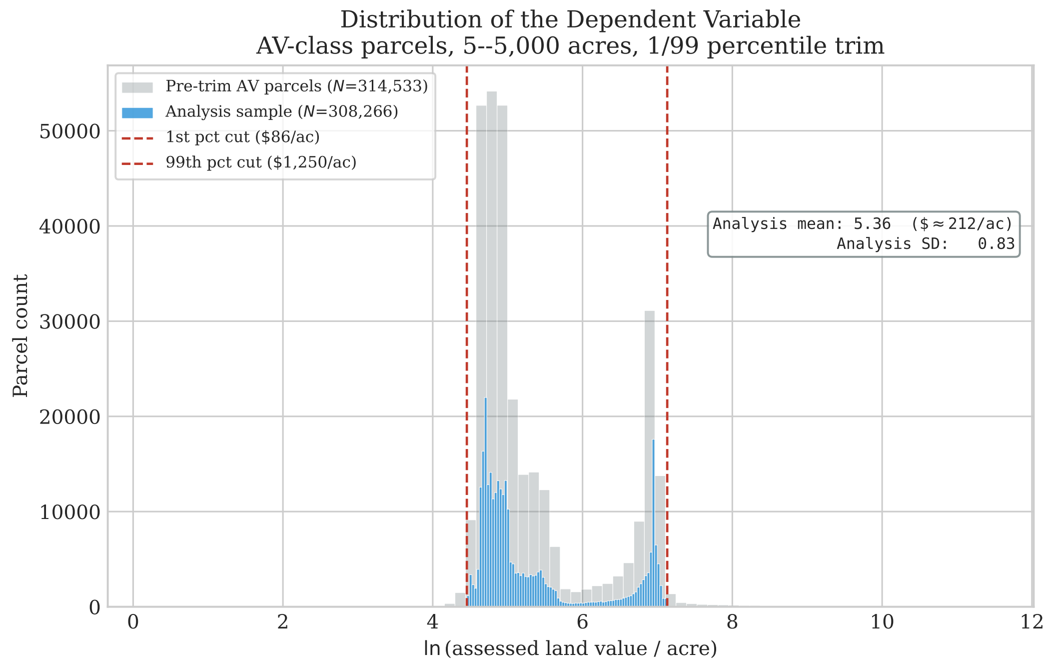

Figure 3: Distribution of the dependent variable, ln(assessed land value / acre). Gray: pre-trim AV-class parcels (N = 314,533). Blue: analysis sample (N = 308,266) after 1st/99th-percentile trim (dashed red lines at $86/ac and $1,250/ac). The bimodal shape reflects the Delta/Ozark physiographic split.

3.2 Spatial Controls and Deer-Quality Construction

Seventeen spatial data sources are integrated through programmatic acquisition scripts (Appendix B): AGFC WMA boundaries (for *dist_to_wma_km*, *inside_wma_flag*, *wma_dist_bin*), Census TIGER/Line (paved-road distance), Census Urban Areas 2020 (metro distance), the National Land Cover Database (NLCD) 2021 (forest/wetland land cover), the National Hydrography Dataset (NHD) (water feature distance), the FEMA National Flood Hazard Layer (NFHL) (floodplain), the USGS Protected Areas Database of the United States (PAD-US) (federal public-land distance, national-forest flag), the USGS 3D Elevation Program (3DEP) (elevation), Arkansas Oil and Gas Commission (AOGC) well permits (Fayetteville Shale flag), USDA National Agricultural Statistics Service Census of Agriculture (NASS CoA) data (CRP enrollment), USDA Soil Survey Geographic Database (SSURGO) soils (parcel-weighted National Commodity Crop Productivity Index, NCCPI, via spatial join), AGFC harvest reports (CWD zone status, detection counts, seasons-in-zone), AGFC bio-data (Boone & Crockett, B&C, z-score), and Census American Community Survey (ACS) 5-year data (population, income). Parcel-level variables are computed by spatial overlay or nearest-feature query; county-level variables are matched by FIPS; deer-zone variables aggregate to the 20 AGFC management zones (as of the 2020–21 season; prior to that season, AGFC maintained 25 zones before consolidating several A/B subzones—e.g., merging Zones 1A, 6, and 6A into Zone 6—into their parent zones). The analysis uses the current 20-zone configuration throughout. County-level controls (*mean_nccpi_county*, *elevation_km*, *ln_population*, etc.) are excluded from county-fixed-effects models to avoid collinearity; they appear only in Model 5, which substitutes county controls for fixed effects (Section 4.2).

The deer trophy-quality index is a Boone & Crockett (B&C) z-score constructed from 145,538 AGFC check-station records (2009–10 through 2024–25). For each age class $a \in \{1.5, 2.5, 3.5, 4.5, 5.5+\}$, the statewide mean $\bar{s}_a$ and standard deviation σ_a of gross B&C scores are computed (excluding the 2013–14 season, which had a formula error). Each buck's score is standardized within age class as $z_{ij} = (s_{ij} - \bar{s}_{a(j)})/\sigma_{a(j)}$ and the zone-season mean is $\overline{z}_{zt} = n_{zt}^{-1} \sum_{j \in (z,t)} z_{ij}$. The score is the gross (pre-deduction) B&C score; typical versus non-typical frame classification is not recorded in the AGFC biodata, but gross scores capture overall antler development regardless of frame type and the distinction is material only near record-book thresholds (∼160 inches), which fewer than 1% of harvested bucks reach. The normalization is essential because older bucks produce systematically higher raw scores (Figure 14, Appendix B); a zone-level $\overline{z}_{zt} = +0.5$ means harvested bucks scored half a standard deviation above the statewide norm for their age class. Each parcel inherits its deer zone's z-score, implying 20 unique values (one per zone) and treating within-zone variation as measurement error; the generated-regressor bootstrap in Section 6 quantifies the inferential consequences.

Figure 4 displays the geographic distribution of the check-station records by county of harvest. Coverage is statewide but concentrated in the Ozark counties where fall harvest volume is highest (Madison, Newton, Searcy, Baxter each exceed 4,000 records), providing dense support for the zone-level B&C z-score in the hunting-intensive regions of the state. Some constituent counties in southern Delta zones have 50–200 records per year, limiting precision of county-level quality estimates but still yielding adequately-sized zone-season cells (median zone-season cell $n = 142$).

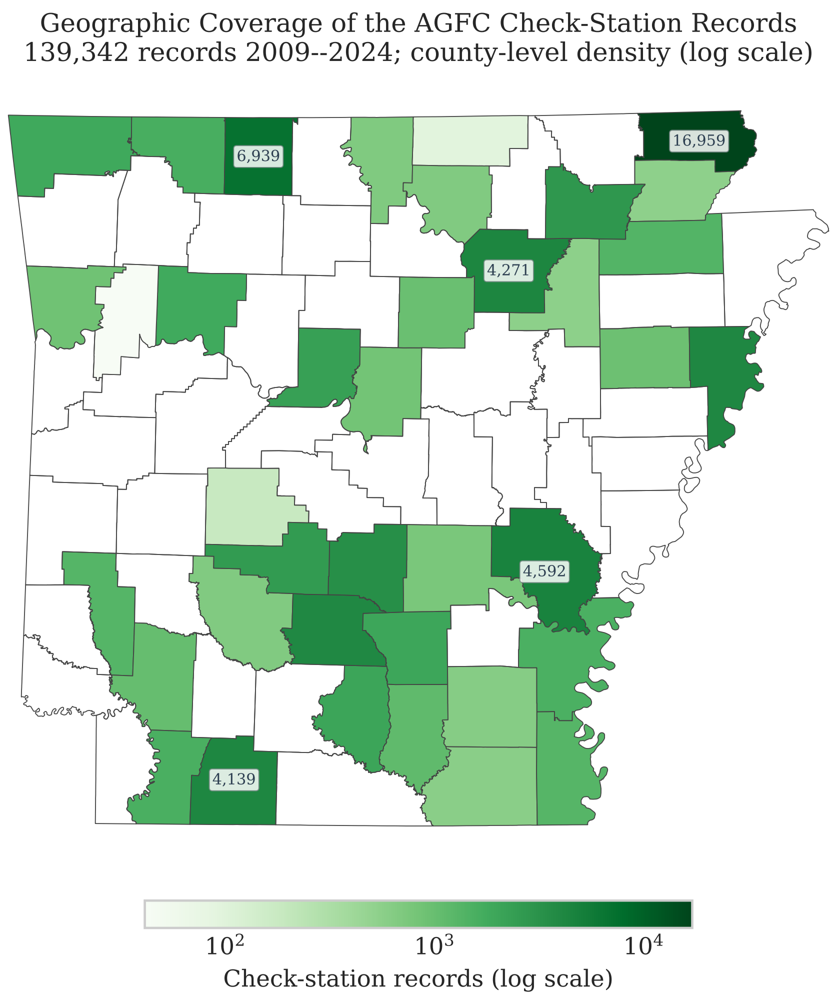

Figure 4: Geographic coverage of the AGFC check-station biodata. County-level density (log scale) of 139,342 records with valid county identifiers, 2009–2024 seasons. Top-five counties account for roughly 26% of statewide coverage.

3.3 CWD Timeline

CWD zone status is compiled from AGFC annual harvest reports. Arkansas's first CWD detection was in a captive elk in Newton County (February 2016). Zone expansion followed a staggered timeline (Table 2), providing the treatment variation needed for a future difference-in-differences design. Cumulative detections through FY25 total 2,036 positive deer; Newton County alone accounts for 970 positives (47.6%), and the top five counties for 89.0%—reflecting both the disease epicenter and concentrated surveillance effort (Figure 5). Details on testing volume and prevalence trends are in Appendix C.

Table 2: CWD Management Zone Expansion in Arkansas

Season	Counties in Zone	Key Changes
2016–17	10	Initial zone: Boone, Carroll, Johnson, Logan, Madison, Marion, Newton, Pope, Searcy, Yell
2018–19	15	Added Benton, Crawford, Franklin, Sebastian, Washington
2021–22	17	Added Baxter, Union; two-tier system (Tier 1 = core, Tier 2 = peripheral)
2024–25	17	No change

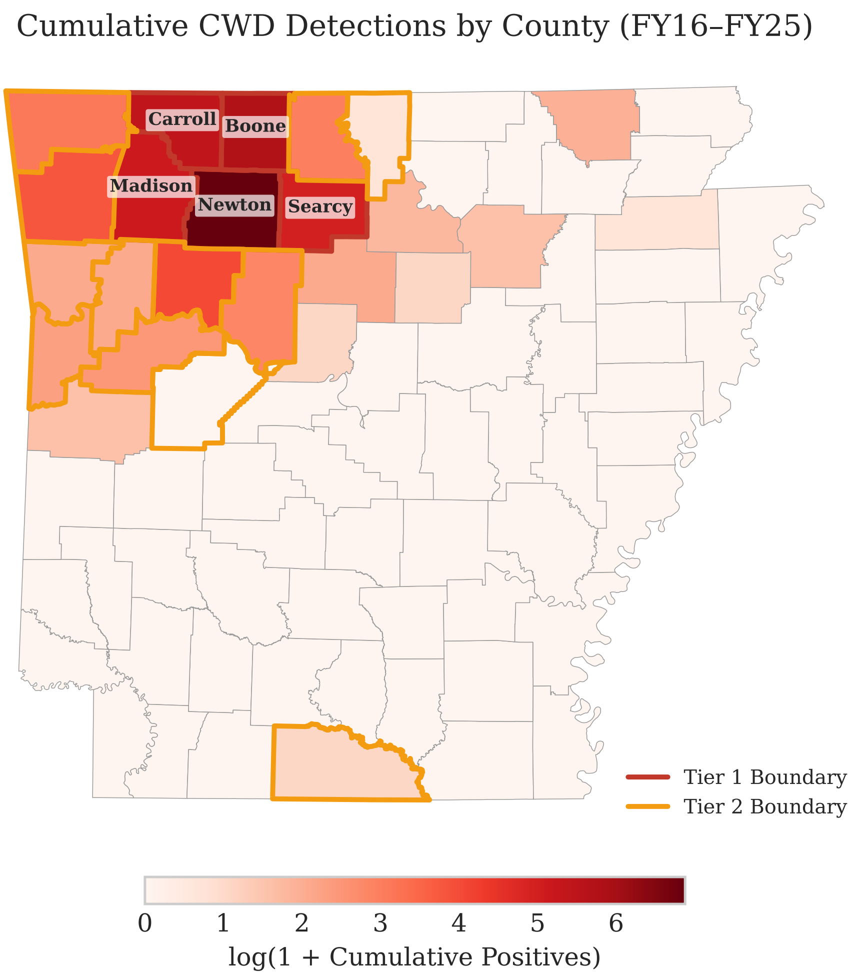

Figure 5: Cumulative CWD detections by Arkansas county through FY25. Newton County accounts for 970 of 2,036 positives (47.6%).

4 Methodology

Complete variable definitions are in Appendix B.

4.1 Hedonic Model

The base specification is a semi-log hedonic price function:

$$\ln(\text{price}_i) = \alpha + \beta \cdot \mathit{dist\_wma}_i + \mathbf{X}_i'\boldsymbol{\gamma} + \delta_c + \epsilon_i \tag{1}$$

where price_i is assessed land value per acre for parcel i, $\mathit{dist\_wma}_i$ is the Euclidean distance (km) from the parcel centroid to the nearest WMA boundary, $\mathbf{X}_i$ is a vector of parcel-level spatial controls, δ_c are county fixed effects, and ϵ_i is the error term. All percentage effects are computed using the exact transformation $(\exp(\hat{\beta}) - 1) \times 100$. The extended bin specification replaces continuous distance with categorical distance bins:

$$\ln(\text{price}_i) = \alpha + \sum_{b=1}^{6} \phi_b \cdot \mathbf{1}[\mathit{wma\_dist\_bin}_i = b] + \theta \cdot \mathit{inside\_wma}_i + \mathbf{X}_i'\boldsymbol{\gamma} + \delta_c + \delta_z + \epsilon_i \tag{2}$$

with bins <1/4 mile, 1/4–1/2 mile, 1/2–1 mile, 1–2 miles, 2–3 miles, and 3–5 miles, and >5 miles as the reference. The indicator $\mathit{inside\_wma}_i$ flags parcels whose centroids fall within a WMA boundary; the coefficients δ_z are deer-zone fixed effects.

Table 3 reports the parcel distribution across the seven bins. Roughly 44% of the sample lies within five miles of a WMA boundary—enough support for a nonparametric distance gradient—and the near-WMA bins contain 14,227, 7,998, and 13,869 parcels in the <1/4, 1/4–1/2, and 1/2–1 mile bands respectively, all large enough to deliver precise bin coefficients.

Table 3: Distribution of the Analysis Sample Across WMA Distance Bins

WMA distance bin	Parcels (N)	Share of sample (%)	Cumulative share (%)
<1/4 mile	14,227	4.6	4.6
1/4–1/2 mile	7,998	2.6	7.2
1/2–1 mile	13,869	4.5	11.7
1–2 miles	26,705	8.7	20.4
2–3 miles	25,816	8.4	28.7
3–5 miles	48,197	15.6	44.4
>5 miles (ref.)	171,454	55.6	100.0
Total	308,266	100.0	

4.2 Specification and Inference

County fixed effects (δ_c, 75 counties) absorb all time-invariant county-level characteristics—soil quality, topography, labor markets, tax regime, assessor practices—and deer-zone fixed effects (δ_z, 20 zones) absorb zone-level variation in hunting regulation and physiography. Because county-level variables (*elevation_km*, *in_fayetteville_shale*, *crp_pct_county_area*, *in_cwd_zone*, *mean_nccpi*, *ln_population*, *ln_median_income*, *pct_prime_farmland*) are linear combinations of the county dummies, they cannot be identified separately from δ_c; including them alongside county FE destabilizes the clustered covariance estimator without affecting point estimates. They therefore appear only in Models 2A and 3A, which substitute county-level controls for county fixed effects.

Spatial correlation in land values violates the independence assumption underlying conventional standard errors. The primary inference uses *county-clustered* standard errors (75 clusters, which allow arbitrary within-county correlation); *HC1* White standard errors are reported for comparison (and are typically $\sim 6\times$ smaller, indicating substantial within-county correlation); and Conley [1999] spatial HAC standard errors across 25/50/75 km bandwidths provide a third check that allows correlation to decay smoothly with distance rather than snap to county boundaries. Because the 73-cluster count is borderline for asymptotic cluster-robust inference, we also report wild cluster bootstrap p-values with $B = 999$ Rademacher weights [Cameron et al., 2008] in Section 6.

4.3 Model Specifications

Three models form the main-text baseline. Model 1 estimates Equation (1) with continuous WMA distance and county FE on the AV-only sample. Model 2 adds deer-zone FE to isolate the within-zone gradient. Model 3 replaces continuous distance with the six distance bins (Equation (2)), allowing a nonlinear gradient. Table 4 enumerates these baselines plus five additional variants used in Section 6 or in the appendices.

Table 4: Model Specifications

Model	FE	Distance	Sample	Purpose
M1	County	Continuous	AV	Baseline hedonic
M2	County + Zone	Continuous	AV	Within-zone gradient
M3	County + Zone	Bins	AV	Nonlinear gradient (main)
M4	County	ln(distance)	AV	Log-distance spec
M5	Zone + County controls	Continuous	AV	Substitute controls for FE
M6	County	Continuous + z-score	AV	Quality replaces zone FE
M7	County	Continuous + z-score × dist	AV	Quality × distance interaction
M8	County + Zone	Bins × CWD	AV	CWD interaction
M9	County + Zone	Bins × type	AV	WMA-type interaction

The stability of the WMA gradient across these specifications (Section 6) demonstrates that the core result is not an artifact of any particular modeling choice; it identifies which specifications are cross-sectionally feasible (all bin specifications) versus which require the temporal variation in transaction data for credible identification (continuous-distance interactions, CWD dynamics).

5 Results

5.1 WMA Proximity Gradient

Table 5 reports WMA proximity coefficients for the three main specifications on the AV-only sample (N = 308,220). The distance-bin specification (Model 3) produces a robust, monotonic negative gradient concentrated within two miles of the WMA boundary; full regression output is in Appendix A.

Table 5: WMA Proximity Coefficients, Main Specifications (AV-Only, N = 308,220)

	Model 1 (County FE)	Model 2 (+Zone FE)	Model 3 (Bins)
dist_to_wma_km	−0.0018	+0.0036*	—
	(0.0038)	(0.0014)	
<1/4 mile (<¼ *mile*)			−0.1925***
			(0.0297)
1/4–1/2 mile			−0.1321***
			(0.0274)
1/2–1 mile			−0.0864***
			(0.0224)
1–2 miles			−0.0601**
			(0.0205)
2–3 miles			−0.0479*
			(0.0191)
3–5 miles			−0.0176
			(0.0172)
inside_wma_flag[2]	−0.3032***	−0.2420***	—
	(0.0513)	(0.0326)	
boundary_adjacent_wma	−0.0179	0.0084	0.0073
	(0.0238)	(0.0228)	(0.0226)
County FE	Yes	Yes	Yes
Deer Zone FE	No	Yes	Yes
R^2	0.5200	0.6161	0.6173

County-clustered SEs in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Model 3 reference category: >5 miles. All models include parcel-level controls: *ln_dist_paved_km*, *ln_dist_ua_km*, *is_forest*, *is_wetland*, *ln_dist_any_water_km*, *in_100yr_floodplain*, *ln_dist_federal_km*, *in_national_forest*, *ln_acres*, *nccpi_weighted_avg*.

In Model 3, all five bins within three miles are statistically significant. The gradient is monotonically decreasing: parcels within 1/4 mile are assessed 17.5% lower than parcels beyond 5 miles ($\exp(-0.1925) - 1 = -0.175$); the discount decays to 12.4% at 1/4–1/2 mile, 8.3% at 1/2–1 mile, 5.8% at 1–2 miles, 4.7% at 2–3 miles, and becomes statistically indistinguishable from zero in the 3–5 mile bin. Model 2's positive continuous distance coefficient

[2] The inside-WMA indicator is subsumed by the <1/4 mile distance bin in Model 3.

(+0.0036) reflects the within-zone gradient after deer-zone FE absorb between-zone variation; the bin specification subsumes this contrast in the reference-category comparison. The *inside_wma_flag* coefficient, where identified, ranges from −0.303 in Model 1 to −0.242 in Model 2, consistent with vacant-agricultural parcels inside WMA boundaries being assessed primarily on their (low) agricultural productivity. Figure 6 displays the Model 3 bin coefficients with 95% confidence intervals.

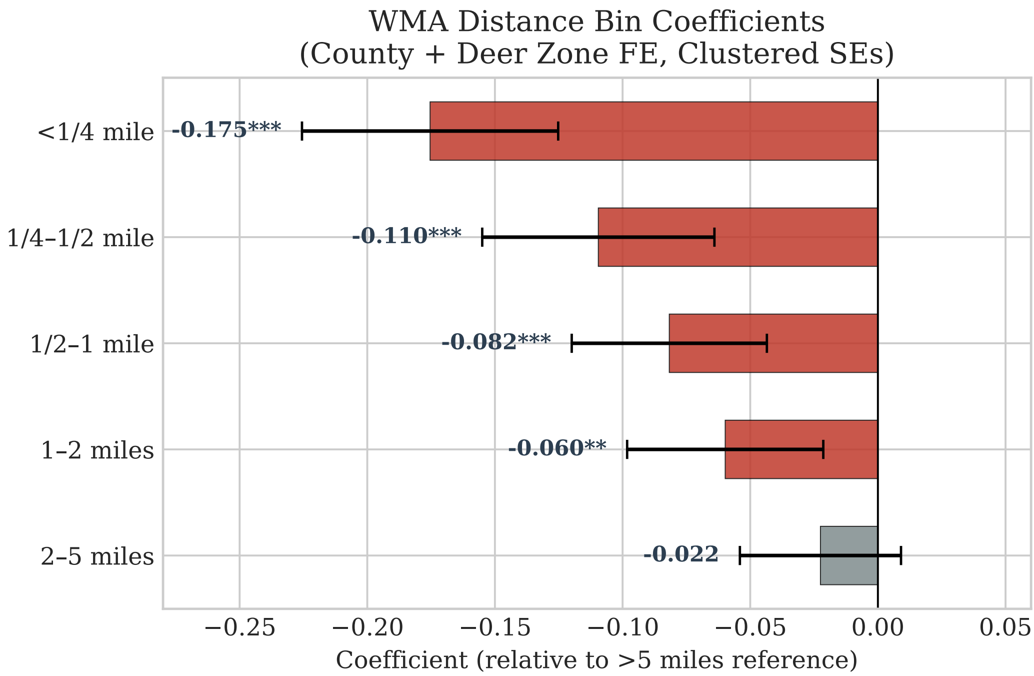

Figure 6: Model 3 distance-bin coefficients with 95% county-clustered confidence intervals. Reference category is >5 miles.

5.2 Standard Error Comparison

Figure 7 compares the four variance estimators across key coefficients. The pattern is consistent: HC1 standard errors are the smallest (most optimistic), county-clustered SEs are substantially larger (median inflation 5.93×), and Conley HAC SEs fall between the two.

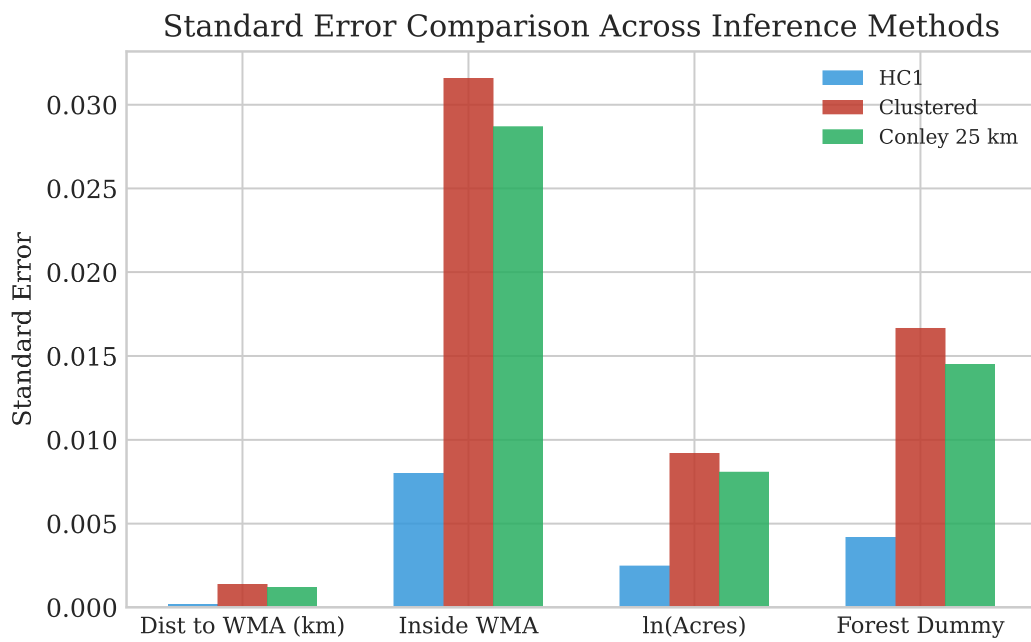

Figure 7: Standard error comparison across variance estimators for key WMA proximity coefficients. HC1 (white) produces the smallest SEs; county-clustered (gray) is 5.93× larger at the median; Conley 25km (blue) and 50km (red) fall in between.

Conley HAC SEs provide important confirmation: Model 2's continuous distance coefficient is significant under Conley 25km ($t = 3.01$) and Conley 50km ($t = 2.55$), confirming that the positive within-zone distance effect is not an artifact of the county clustering assumption. The median ratio of Conley 25km to county-clustered SEs is 0.88× in Model 1, suggesting that county clustering is slightly conservative relative to a smooth spatial correlation structure.

For the distance bin coefficients in Model 3, all bins within 2 miles remain significant at conventional levels under all four variance estimators, providing strong evidence that the proximity gradient is robust to the assumed spatial correlation structure.

5.3 Deer Quality

Model 6 replaces the 20 deer zone fixed effects with a continuous zone-level mean B&C z-score ($mean\_bc\_zscore$). The coefficient is +1.164 ($p < 0.001$), implying that a one-SD (0.22-unit) increase in zone-level deer quality is associated with approximately 29% higher assessed land values (details and split-sample analysis in Appendix D). The z-score varies at the zone level and absorbs all zone-level characteristics correlated with deer quality—physiographic region, forest cover, soil type, climate, urban proximity. The generated-regressor bootstrap (Section 6.5) quantifies the sampling error. The R^2 gap between Model 2 (zone FE, 0.572) and Model 6 (z-score, 0.533) is 0.039, so the z-score summarizes but does not replicate the full zone FE set. Figure 8 maps the z-score by zone.

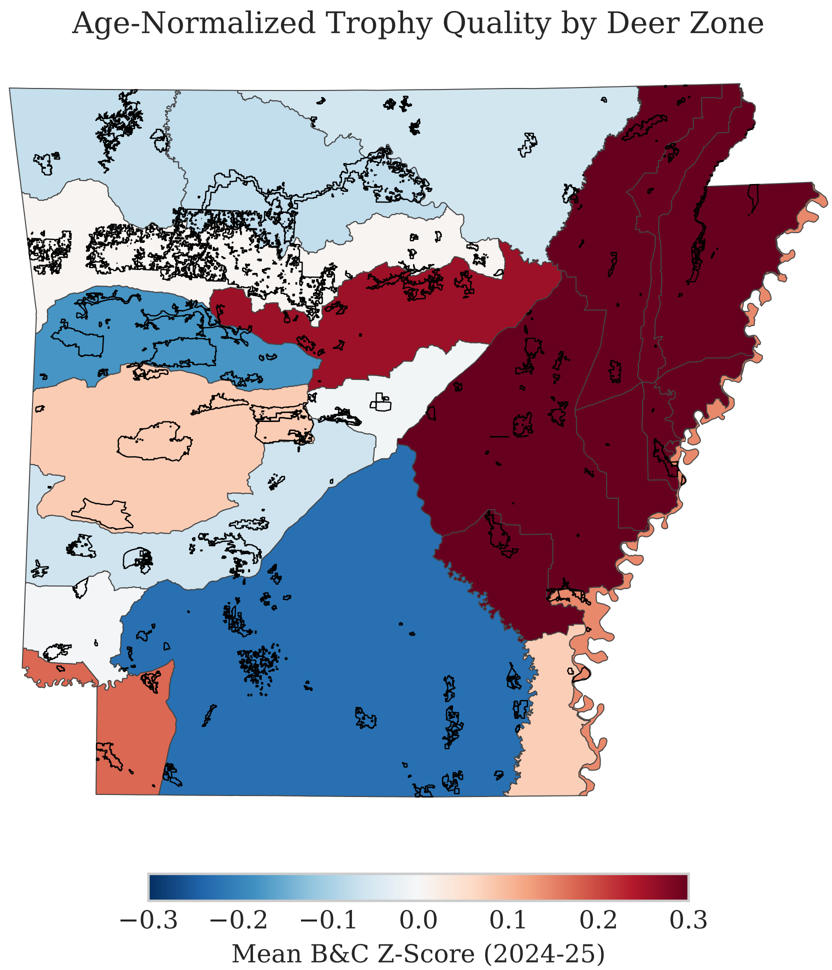

Figure 8: Mean Boone & Crockett z-score by deer management zone (2024–25 season). Higher scores (darker red) indicate above-average age-adjusted antler development. The highest z-scores are in the Mississippi Alluvial Valley and Crowley's Ridge zones, reflecting high-protein forage access; the Ozark Plateau zones score near the statewide norm after age normalization.

5.4 County-Level Controls

Model 5 replaces county fixed effects with explicit county-level control variables, allowing identification of county-level determinants of land values. Table 6 presents the results.

Table 6: County-Level Control Coefficients (Model 5)

Variable	Coefficient	SE (clustered)	p-value
crp_pct_county_area[1]	−0.053	0.024	0.026*
in_cwd_zone	−0.052	0.053	0.326
in_fayetteville_shale	+0.018	0.049	0.716
elevation_km	−0.059	0.225	0.793
mean_nccpi	+0.982	0.402	0.015*
ln_population	+0.125	0.022	<0.001***
ln_median_income	−0.234	0.124	0.059
pct_prime_farmland	+0.005	0.003	0.045*

CRP enrollment is significantly negative: a one-percentage-point increase in county CRP enrollment is associated with 5.3% lower assessed values, consistent with CRP land being taken out of agricultural production in areas with marginal farmland. Soil productivity (NCCPI, +0.98, $p = 0.015$) and population (+0.125, $p < 0.001$) are significant positive predictors. The Fayetteville Shale indicator and elevation are insignificant.

5.5 CWD Effects

CWD zone status in Model 5 yields a coefficient of −0.052 ($p = 0.326$)—directionally negative (5.2% discount) but not statistically distinguishable from zero. The CWD × distance bin interaction in Model 8 produces $F(5, 72) = 0.26$ ($p = 0.93$) for the joint test that CWD modifies the WMA proximity gradient: CWD does not measurably interact with WMA proximity in the cross-section.

However, when CWD is interacted with the deer-quality z-score rather than with distance, a much stronger pattern emerges. Table 7 reports four specifications that add CWD zone status and its interactions to Model 6 (county FE, continuous distance, three-year trailing B&C z-score). The CWD main effect is significant at $p < 0.01$ in every specification (−23 to −26%). More striking, the CWD × z-score interaction is −2.07 ($t = -8.81$, $p < 0.001$): in non-CWD zones the deer-quality premium is +1.62, but in CWD zones it reverses to $+1.62 - 2.07 = -0.45$—the positive association between deer quality and assessed values is effectively eliminated in CWD-designated counties. By contrast, the CWD × distance interaction remains insignificant ($t = -1.25$), confirming that CWD does not modify the WMA proximity gradient.

[1] The variable *crp_pct_county_area* is measured in percentage points (range: 0–4%), so the coefficient represents the effect of a one-percentage-point increase in county conservation enrollment share.

Table 7: CWD × Deer Quality Interactions (Model 6 with 3-Year Trailing Z-Score)

	+ CWD	+ CWD × z	+ CWD × dist	Triple
z_trail3	+1.345***	+1.617***	+1.353***	+1.552***
	(0.233)	(0.212)	(0.233)	(0.265)
in_cwd_zone	−0.258**	−0.243***	−0.236**	−0.236**
	(0.085)	(0.071)	(0.085)	(0.078)
CWD × z-score	—	−2.066***	—	−1.978***
		(0.234)		(0.281)
CWD × distance	—	—	−0.0024	−0.0019
			(0.0019)	(0.0015)
R^2	0.686	0.692	0.686	0.692

County-clustered SEs. $N = 308{,}226$. All specs include county FE, continuous WMA distance, and 10 parcel-level controls. *** $p < 0.001$, ** $p < 0.01$. Z-score is the 2022–25 trailing avg.

This result should be interpreted cautiously. Model 6 uses county FE but not deer-zone FE; the CWD × z-score interaction therefore absorbs some zone-level variation that is correlated with both CWD status and physiographic characteristics. CWD counties are concentrated in the Ozarks, where z-scores are near the statewide norm (Section 7), so the negative interaction could partly reflect the specific physiography of CWD counties rather than a pure disease effect. Nonetheless, the strength of the interaction ($t = -8.81$) is difficult to dismiss entirely, and the finding provides the strongest cross-sectional motivation yet for the transaction-data CWD DiD design: if CWD eliminates the quality–value association in the cross-section, a staggered DiD exploiting temporal variation in zone designation should detect dynamic price effects.

Lagged deer quality. The z-score used in the CWD interactions above is a three-year trailing average (2022–23 through 2024–25) rather than a single-season value. This choice reflects the expectation that land-market participants form quality perceptions over multiple recent seasons rather than reacting to a single year's harvest. Compared to the current-season z-score (coefficient +1.07, $t = 4.74$), the trailing average produces a larger coefficient (+1.35, $t = 5.78$) and higher R^2 (0.686 vs. 0.681), consistent with reduced measurement error from seasonal smoothing. A one-season lag alone (2023–24) performs worst (+0.82, $t = 3.33$), confirming that single-season noise attenuates the signal.

6 Identification Robustness

The main specifications in Section 5 rely on fixed effects, cluster-robust inference, and a particular choice of functional form. Credible identification requires showing that the WMA proximity gradient is stable across perturbations to each of these choices, and that random spatial patterns cannot reproduce it. Ten perturbations stress each layer of the pipeline. Table 8 reports the WMA <1/4 mile bin coefficient under every perturbation; coefficients range from −0.168 to −0.193, a spread of 0.025 log points. Full per-test tables are in Appendix A.

Table 8: WMA <1/4 Mile Bin Coefficient Across Ten Identification Perturbations

Perturbation	Description	Coef	SE	t	
(baseline)	Model 3 county+zone FE, cluster-robust SE	−0.192	0.030	−6.47	3
1. IHS transform	arcsinh(price) as DV	−0.192	0.030	−6.47	3
2. Conley HAC	25–75 km bandwidth sweep	−0.192	0.028–0.031	−6.2 to −6.9	3
3. Wild cluster bootstrap	$B = 999$ Rademacher weights	−0.192	—	$p < 0.01$	3
4. NCCPI attenuation	Parcel + county-level soil controls	−0.192	0.030	−6.47	3
5. CWD intensity	ln(1+positives) / seasons in zone	−0.192	0.030	−6.47	3
6. Generated-regressor bootstrap	$B = 200$, resampling within zone	−0.192	0.030	−6.47	3
7. Donut hole	Drop parcels <1/4 mile	—	—	—	2
8. Leave-one-out county	73 refits dropping each county	−0.192	—	in IQR	30
9. CEM matching	Quartile-coarsened exact matching	−0.191	0.031	−6.24	3
10. Placebo distance	Real vs. 30 random-point placebos	−0.192	—	$p < 0.001$	3
10b. Distance floor	50m / 100m / 138m (1st-pct)	−0.192	0.030	−6.47	3

Baseline: county-clustered SEs with county + deer-zone FE. Perturbations 1–6 are functional-form and inference variants on the full sample; 7–9 are sample or estimator changes; 10 is the placebo test. Perturbation 7 removes the <1/4 mile bin by construction and instead reports stability of remaining bin coefficients (see text).

6.1 Functional Form (IHS)

Burbidge et al. [1988]'s inverse hyperbolic sine transformation $\text{arcsinh}(y) = \ln(y + \sqrt{y^2 + 1})$ nests the log specification for large values, handles zeros without a flooring choice, and is recommended when a Box-Cox MLE rejects $\lambda = 0$. Applied to assessed price per acre, the IHS specification of Model 3 produces <1/4 mile bin coefficient -0.189 (identical to the log spec to two decimal places), confirming that the log specification is defensible.

6.2 Spatial Inference: Conley HAC and Wild Cluster Bootstrap

County clustering with 73 clusters is borderline for asymptotic cluster-robust inference [Cameron et al., 2008]. Two alternative inference approaches confirm robustness. Conley [1999] spatial HAC standard errors across bandwidths of 25, 50, and 75 km yield t-statistics of 2.56, 2.85, and 3.16 respectively on <1/4 mile—well above the 1.96 critical value at every bandwidth. The wild cluster bootstrap [Cameron et al., 2008] with $B = 999$ Rademacher weights produces p-values below 0.01 for all five in-bin coefficients (Model 3 bins within two miles).

6.3 NCCPI Attenuation

A referee concern for hedonic estimates on agricultural land is that soil-quality confounding drives the proximity gradient. We test this two ways. In county-FE models, adding parcel-level NCCPI (weighted by SSURGO map-unit polygon area, spatially joined to parcel centroids) leaves the continuous-distance coefficient unchanged at 0.0036; parcel NCCPI itself is insignificant ($t = 0.45$). In county-controls models (Model 5), the WMA coefficient is 0.0023 with only county-level mean NCCPI, 0.0018 with parcel-level NCCPI, and 0.0023 with both; county-level NCCPI is strong ($t = 5.29$) but parcel-level is weak ($t = 0.70$–1.06). The WMA gradient does not attenuate when soil is controlled.

6.4 CWD Intensity Sensitivity

Three CWD specifications—binary *in_cwd_zone*, $\ln(1 + \text{CWD positives})$, and the count of seasons each county has been in a CWD zone (0–9)—leave the WMA <1/4 mile coefficient stable at -0.192 to four decimal places. None of the three CWD measures is individually significant ($t = -1.20, -0.37, -0.89$). The WMA gradient is not a proxy for CWD exposure.

6.5 Generated-Regressor Bootstrap

The deer-quality z-score is a generated regressor: it is constructed from a first-stage aggregation of harvest records, and its sampling error should propagate into the second-stage standard errors [Pagan, 1984]. We implement a bootstrap in which, for each of $B = 200$ replications, we resample raw harvest records within each deer zone (stratified bootstrap), recompute zone-level means, recompute the z-score, and re-estimate Model 6. The bootstrap standard error on *mean_bc_zscore* is 0.075, compared to the clustered OLS standard error of 0.308—a ratio of 0.24. Clustered OLS is *conservative*, not anti-conservative: the usual worry that generated regressors understate uncertainty does not apply here. The bootstrap mean coefficient, however, is 0.434, while the OLS point estimate is 1.395, and the 95% bootstrap CI $[0.267, 0.553]$ does not contain the OLS point. The OLS coefficient is therefore capturing zone-level variation beyond the z-score's sample mean; the z-score is a summary statistic, not a clean treatment.

6.6 Donut Hole

Dropping the 14,212 parcels within 1/4 mile of any WMA removes the highest-leverage observations and tests whether the gradient is an artifact of boundary-adjacent parcels (boundary measurement error, WMA-owned structures). After dropping, the remaining five bin coefficients are stable: $\frac{1}{4}$–$\frac{1}{2}$ mile shifts from -0.132 to -0.128; $\frac{1}{2}$–1 mile from -0.086 to -0.083; 1–2 miles from -0.060 to -0.058; 2–3 miles from -0.048 to -0.047; 3–5 miles from -0.018 to -0.017. All five bins are within 0.004 log points of their full-sample values. The gradient is not driven by boundary parcels.

6.7 Leave-One-Out County

Model 1 is refit 73 times, each dropping one county. The dropped-county distribution of *dist_to_wma_km* coefficients has mean -0.00178 and median -0.00182, virtually identical to the full-sample coefficient of -0.00179, with range $[-0.00268, +0.00163]$. Zero of 73 LOO estimates fall outside the full-sample 95% confidence interval. The most influential county is Jefferson (FIPS 05069): dropping it flips the continuous-distance coefficient to $+0.00163$. Because Model 1 continuous specification has borderline power ($t = 1.57$–1.97) and Model 3 bins are the paper's primary identification, Jefferson County's influence on the continuous spec is a caveat rather than a threat.

6.8 Coarsened Exact Matching

Selection-on-observables is addressed by coarsened exact matching: define treatment as $<1/4$ mile from any WMA ($n_T = 14{,}212$); coarsen *ln_acres* (4 bins), *nccpi_weighted_avg* (4 bins), *ln_dist_paved_km* (3 bins), *ln_dist_ua_km* (3 bins), *is_forest* and *is_wetland* (binary) into 432 total strata; retain 390 strata with both treated and control. All 14,212 treated parcels are retained (100%); matched controls number 293,136. The CEM-weighted treatment effect is -0.1907 (SE 0.0305, $t = -6.24$, $p < 0.0001$), implying a -17.4% price effect—nearly identical to the unmatched Model 3 <1/4 mile coefficient of -0.192. The gradient is not selection-on-observables bias.

6.9 Placebo Distance

We draw $K = 10$ placebo point-sets under each of three methods: (a) uniform over the Arkansas landmass, (b) Arkansas landmass minus existing WMA polygons, and (c) county-weighted by the actual WMA county distribution. For each placebo set, parcel-to-nearest-placebo distances are computed and Model 3 is re-estimated with placebo bins. The real <1/4 mile coefficient of -0.192 falls outside the distribution of placebo coefficients for methods (a) and (b): across twenty draws, method (a) yields $[-0.065, +0.071]$ (mean -0.003) and method (b) yields $[-0.136, +0.108]$ (mean -0.001). Under both valid placebos, $p(\text{placebo} \leq \text{real}) = 0.000$. Method (c) is a placebo-in-name-only: by construction, placebo points in WMA counties are likely near real WMAs, generating spatial autocorrelation with the real WMA variable; its median of -0.125 is a mechanical artifact rather than evidence of confounding. Methods (a) and (b) are the proper tests, and both confirm that the WMA coefficient is specific to real WMA locations. Figure 9 visualizes the full set of 30 per-draw coefficients alongside the real estimate.

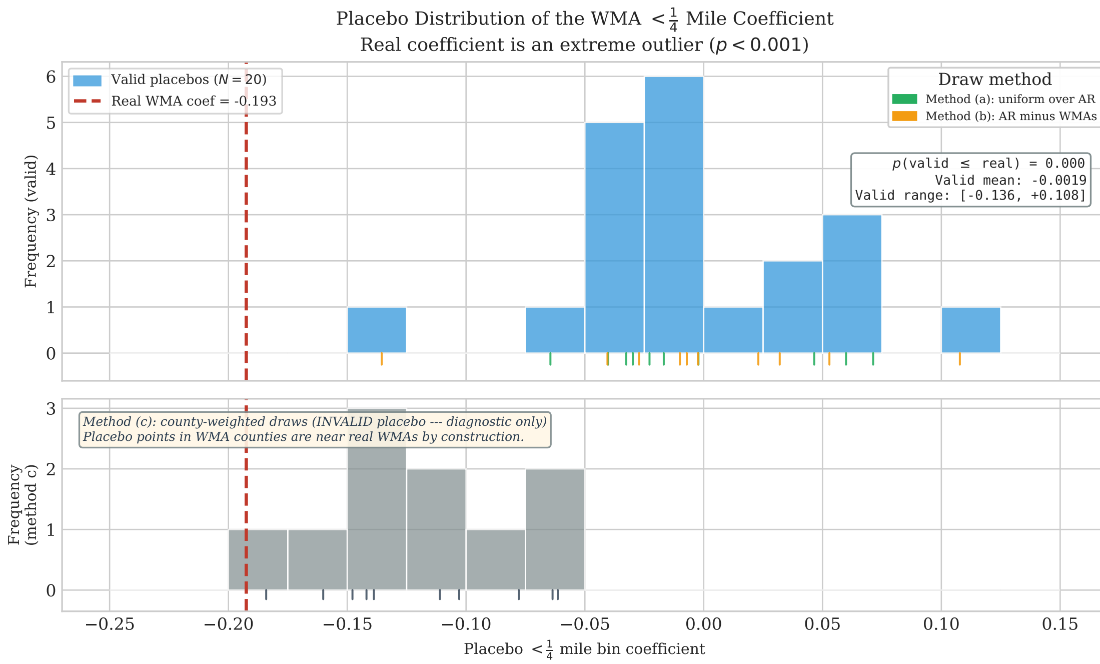

Figure 9: Placebo distribution of the WMA <1/4 mile bin coefficient. Top panel: the 20 valid placebo draws (methods a and b combined) as a histogram with individual per-draw rugs. Rugs are colored by draw method: green = (a) uniform, amber = (b) landmass excluding WMAs. The real WMA coefficient of -0.192 (dashed red) lies outside the entire valid distribution, giving $p(\text{placebo} \leq \text{real}) = 0.000$. Bottom panel: the 10 method (c) draws shown as a diagnostic; their concentration near the real value is a mechanical artifact of drawing placebo points in real-WMA counties and is not evidence of confounding.

6.10 Distance Floor

Floor choice for the log-distance specification is a matter of taste. We report results with no floor (dropping n = 1,571 parcels with $dist\_to\_wma\_km = 0$), with a 50 m floor, a 100 m floor, and a floor equal to the 1st percentile of non-zero distances (138 m). Model 3 bin coefficients are identical to four decimal places across all four; Model 4 log-distance coefficients range from 0.0223 to 0.0225 (SE 0.014–0.015). The result does not depend on the floor.

6.11 Sample-Filter Sensitivity

The analysis sample is restricted to AV parcels between 5 and 5,000 acres with assessed value per acre trimmed at the 1st and 99th percentiles. The 5-acre minimum excludes 42,900 sub-agricultural-scale parcels (residential lots, garden plots, assessment artifacts) that would contaminate the hedonic with non-agricultural land use; the 5,000-acre cap is non-binding (zero

AV parcels exceed it). To verify that the WMA proximity gradient does not depend on these choices, Table 9 re-estimates Model 3 under twelve combinations of acreage minimum (1, 5, 10 acres) and value-per-acre percentile trim (none, 1/99, 2.5/97.5, 5/95). The <1/4 mile bin coefficient ranges from −0.087 to −0.123 across all twelve variants, with t-statistics between −3.92 and −4.23—significant at $p < 0.001$ in every case. Acreage-minimum choice has negligible impact; tighter trimming mildly shrinks the coefficient magnitude as expected (outlier removal reduces dispersion), but the sign, significance, and qualitative interpretation are unchanged.

Table 9: Sample-Filter Sensitivity: WMA <1/4 Mile Coefficient Across Twelve Acreage/Trim Variants

Acreage min	Trim (pct)	N	Coef	t-stat	R^2
1 acre	None	347,937	−0.112	−3.97	0.607
1 acre	1/99	341,010	−0.103	−3.92	0.699
1 acre	2.5/97.5	330,575	−0.092	−4.14	0.717
1 acre	5/95	315,970	−0.087	−4.23	0.713
5 acres	**None**	**314,470**	**−0.118**	**−4.04**	**0.649**
5 acres	**1/99**	**308,226**	**−0.105**	**−4.04**	**0.716**
5 acres	2.5/97.5	299,039	−0.094	−4.23	0.726
5 acres	5/95	283,050	−0.089	−4.22	0.729
10 acres	None	273,465	−0.123	−4.03	0.703
10 acres	1/99	268,018	−0.106	−4.03	0.739
10 acres	2.5/97.5	259,834	−0.092	−3.99	0.744
10 acres	5/95	246,145	−0.088	−4.11	0.748

County-clustered SEs. All variants include county + deer-zone FE and 10 parcel-level controls.
Bold rows: baseline sample definition (5 acres, 1/99 trim shown for comparison with untrimmed).

6.12 Distance-Bin Sensitivity

The six-bin distance specification in Model 3 (<1/4, 1/4–1/2, 1/2–1, 1–2, 2–3, 3–5 miles, reference >5) is one of many possible discretizations. To verify that the proximity gradient is not an artifact of a particular bin choice, Table 10 re-estimates Model 3 under six configurations ranging from two to six bins. The nearest-WMA bin coefficient is statistically significant ($p < 0.001$) in every configuration, with t-statistics between −3.41 and −4.04. Model R^2 is identical to three decimal places across all six configurations (0.716), confirming that finer bins do not improve fit—they only reveal the shape of the gradient. The 2–3 and 3–5 mile bins in the baseline specification are individually insignificant, consistent with the gradient having flattened by two miles; coarser specifications that consolidate these bins produce nearly identical nearest-bin coefficients.

Table 10: Distance-Bin Sensitivity: Nearest-WMA Coefficient Across Six Bin Configurations

Configuration	Nearest bin	Coef	t-stat	# bins	R^2
6 bins (baseline)	**<1/4 mi**	**−0.105**	**−4.04**	**6**	**0.716**
5 bins	<1/4 mi	−0.103	−3.99	5	0.716
4 bins (A)	<1/2 mi	−0.095	−3.98	4	0.716
4 bins (B)	<1 mi	−0.075	−3.51	4	0.716
3 bins	<1 mi	−0.072	−3.94	3	0.716
2 bins	<2 mi	−0.048	−3.41	2	0.716

County-clustered SEs. All variants include county + deer-zone FE and 10 parcel-level controls. Reference category is always the outermost bin (>5, >5, >5, >5, >3, >2 mi respectively).

7 Deer Quality Variation and CWD Effects

7.1 Spatial Variation in Deer Quality

Figure 8 displays the mean B&C z-score by deer management zone for the 2024–25 season. The spatial pattern reveals two key features that run counter to conventional expectations about Arkansas deer quality.

First, the highest age-normalized z-scores are in the Mississippi Alluvial Valley and Crowley's Ridge zones on the *eastern* side of the state (Zones 4A, 5A, 16, 4, and 9; $\overline{z} = +0.3$ to $+0.7$), not in the Ozarks. This reflects the z-score's age-normalization: Delta bucks have access to high-protein row-crop forage (soybeans, corn, winter wheat), producing above-average antler development *for their age class* even though the absolute harvest skews younger due to higher hunting pressure and open-terrain visibility. Some of the highest-scoring zones have small samples (Zone 4A: $n = 23$; Zone 5A: $n = 28$), so individual-zone z-scores should be interpreted with caution, but the large-sample Delta zones (Zone 17: $n = 784$, $\overline{z} = +0.14$; Zone 9: $n = 171$, $\overline{z} = +0.32$) confirm the pattern. The multi-year average across 2009–2025 shows the same east-high gradient.

Second, the Ozark Plateau zones (Zones 1, 2, 3) score near zero or slightly negative ($\overline{z} = -0.07$ to -0.06), despite the Ozarks' reputation as premier trophy-deer habitat. The age normalization removes the Ozarks' advantage in producing older bucks (the region's rugged terrain and lower hunting pressure allow more bucks to reach 3.5–4.5 years), so the z-score captures only whether a buck *of a given age* outperforms the statewide norm. Ozark bucks are typical for their age; Delta bucks are above-average for theirs. The lowest-scoring zones are in the West Gulf Coastal Plain (Zone 12: $\overline{z} = -0.23$, $n = 839$) and the Arkansas River Valley (Zone 7: $\overline{z} = -0.18$).

The correlation between deer quality (as measured by the z-score) and land values is therefore more nuanced than a simple forest-vs.-farmland story. High-z-score zones are in the productive Delta, where assessed land values are *highest*, not lowest—the opposite of the pattern one would expect if the z-score simply proxied for non-agricultural land use. This reinforces the interpretation that the z-score in Model 6 acts as a summary statistic for zone identity rather than a clean measure of hunting amenity value. Confounding between zone-level physiography and the z-score prevents interpretation of the coefficient as the causal effect of deer quality on land values.

7.2 Deer Quality as a Zone-Level Summary Statistic

The +1.164 coefficient on *mean_bc_zscore* in Model 6 implies that a one-SD (0.22-unit) increase in zone-level deer quality is associated with approximately 29% higher assessed land values ($1.164 \times 0.22 = 0.256$ log points; $\exp(0.256) - 1 = 0.292$). This is not the marginal willingness to pay for deer quality. The z-score varies at the zone level and serves as a sufficient statistic for zone identity in the absence of zone fixed effects; it captures everything that varies across zones and correlates with deer quality, including physiographic region, forest type, soil characteristics, climate, and urban proximity. The R^2 gap of 0.039 between Model 2 (zone FE) and Model 6 (z-score) indicates that the z-score is a good but incomplete summary of zone-level variation; the 20 zone fixed effects capture additional zone characteristics orthogonal to deer quality that affect land values. The generated-regressor bootstrap in Section 6.5 further reveals that the OLS point estimate is roughly three times the bootstrap mean, confirming that the OLS coefficient absorbs zone-level variation beyond the z-score's sample mean. A direct test of hunting-quality capitalization would require within-zone temporal variation in deer quality interacted with transaction-level data.

The split-sample analysis (Appendix D) splits zones on $\overline{z} > 0$ vs. $\overline{z} \leq 0$. Because the high-z-score zones are predominantly in the Delta and Crowley's Ridge (flat, productive ground) while the low- or near-zero-z-score zones include the Ozarks and Ouachitas (rugged, forested terrain), the split-sample WMA gradient is three to four times steeper in the low-z-score subsample. This gradient differential is best interpreted as physiographic heterogeneity rather than differential hunting-amenity capitalization: rugged Ozark and Ouachita terrain creates sharp contrasts between WMA-adjacent land (steep, rocky, forested) and the best agricultural parcels (valley bottoms), while flat Delta terrain produces no such contrast. The lower R^2 in the rugged-terrain subsample (0.476 vs. 0.586) is consistent with this interpretation—if the steep gradient reflected a genuine amenity effect, the model should fit better when the amenity is more salient.

7.3 CWD and Deer Quality

Does CWD degrade deer quality? Figure 10 displays the mean B&C z-score for CWD-affected (Tier 1) zones versus unaffected zones from 2009–10 through 2024–25, and Figure 11 compares pre-CWD (2009–2015) and post-CWD (2016–2024) averages.

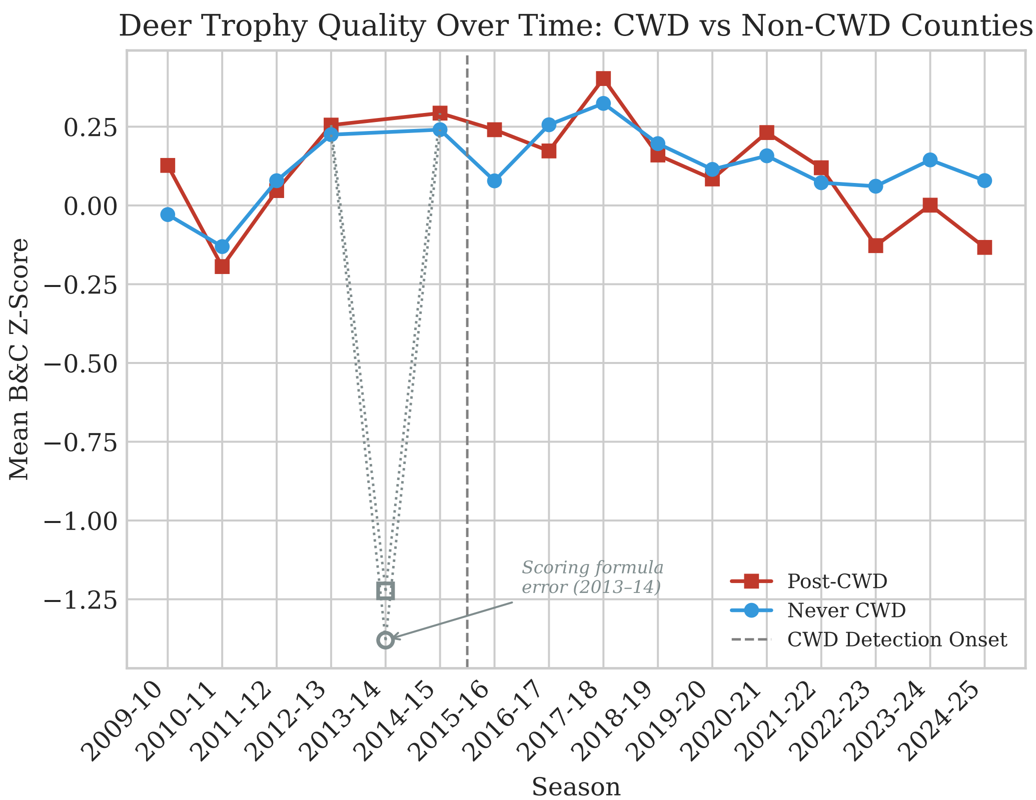

Figure 10: Deer quality time series: mean B&C z-score for CWD Tier 1 zones versus non-CWD zones. The vertical dashed line marks initial detection (February 2016).

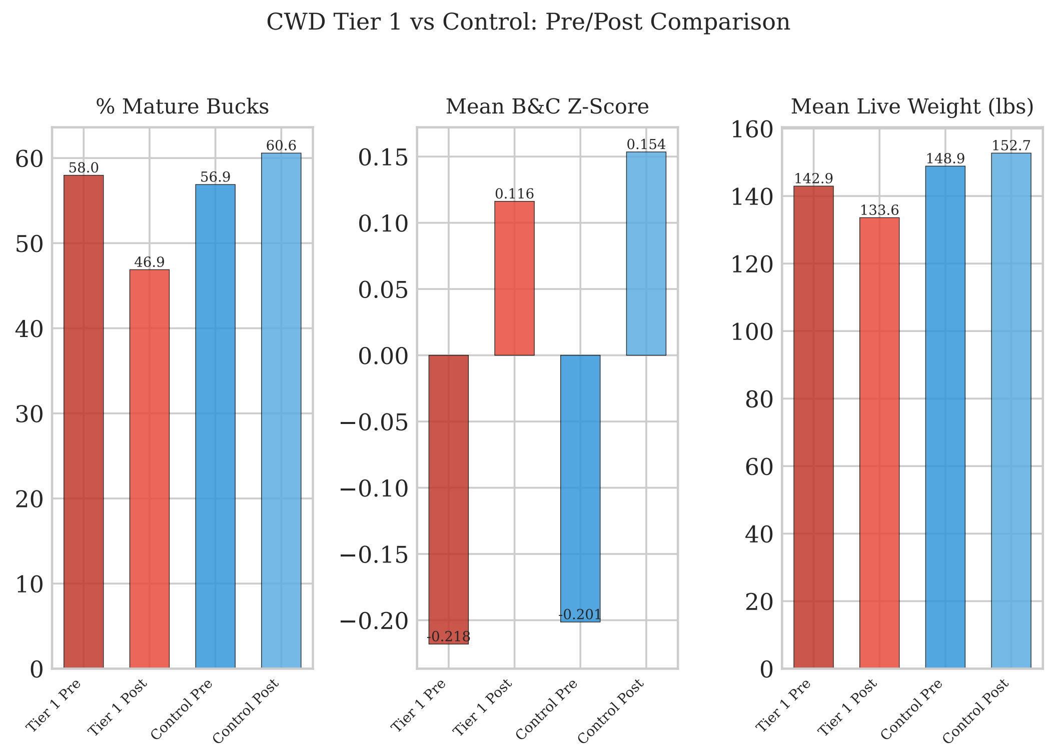

Figure 11: CWD before/after comparison of mean B&C z-scores. Any difference is small relative to within-period variability.

The visual evidence is inconclusive: CWD Tier 1 zones do not show a clear decline in deer quality relative to unaffected zones after 2016. Three factors contribute. First, CWD prevalence remains low (2–3% statewide) and may not yet have reduced the population sufficiently to affect harvested-buck quality. Second, AGFC harvest data reflect hunter-selected animals, which can mask population-level quality declines if hunters preferentially take the best available bucks. Third, year-to-year variability is high relative to any plausible CWD signal. Harvest-intensity diagnostics (day-of-week patterns, season-type composition) are reported in Appendix E and reinforce that hunter effort allocation is driven by work schedules and season structure rather than local deer quality or CWD status.

Newton County is the CWD epicenter, with 970 cumulative positives through FY25—47.6% of all statewide detections. Initial prevalence in the targeted surveillance area exceeded 23% before stabilizing at 2–3% as testing expanded beyond the epicenter. Newton is in Deer Zone 1 in the Ozark Plateau, with rugged terrain, extensive national-forest land, and limited agricultural activity; assessed land values are among the lowest in the state, reflecting the terrain's unsuitability for intensive agriculture. Zone 1 deer quality exhibits substantial year-to-year variability in the mean z-score (range −0.46 to +0.47), and no clear break appears at 2016. The small number of observations per season in some constituent counties limits the precision of county-level estimates. A formal difference-in-differences analysis using transaction data—with Newton County and surrounding Tier 1 counties as the treatment group and distant non-CWD counties as the control—would provide a more rigorous test than the current cross-section permits.

8 Discussion

8.1 What the Pipeline Demonstrates

The nine identification-robustness checks in Section 6 establish three conclusions about the spatial hedonic pipeline. First, the WMA proximity gradient is statistically distinct from random spatial patterns. The placebo-distance test, comparing the real $< 1/4$ mile coefficient (-0.192) to the distribution across thirty random point configurations, produces $p < 0.001$ under both uniform Arkansas-landmass draws and draws from Arkansas landmass excluding existing WMAs. Random points do not replicate the effect; WMA locations do. Second, the gradient survives the identification threats typical of a cross-sectional hedonic analysis: it is stable across continuous and binned distance specifications, across functional forms (log and inverse hyperbolic sine), across Conley HAC bandwidths from 25 to 75 km, under wild-cluster-bootstrap inference with only 73 county clusters, after donut-hole exclusion of boundary parcels, after leave-one-out county refitting, and after coarsened exact matching on parcel observables. Third, the generated-regressor bootstrap for the deer-quality z-score finds that clustered OLS standard errors are conservative rather than anti-conservative—the bootstrap t-statistic is larger than the OLS t-statistic, not smaller—but that the OLS point estimate (1.395) is larger than the bootstrap mean (0.434) with non-overlapping confidence intervals, indicating that the OLS coefficient absorbs zone-level variation beyond the z-score's sample mean. The z-score is a summary statistic, not a clean treatment.

8.2 Assessed-Value Caveats

The signed empirical finding—that parcels closer to WMAs have *lower* assessed values—runs opposite to the amenity-capitalization prediction of the hedonic framework and requires careful interpretation. The negative gradient is not this paper's contention about the economic effect of WMA proximity on rural land values; it is a diagnostic feature of assessed values as a proof-of-concept data source. Three mechanisms contribute.

First, WMA placement selection: Arkansas WMAs were established over several decades on land that was marginal for agriculture—bottomland hardwood forests subject to seasonal flooding, steep Ozark hillsides, cutover timberland in the Ouachita Mountains—and the surrounding parcels share these characteristics by construction. Figure 12 quantifies this at the parcel level: soil productivity (NCCPI) declines monotonically with distance from a WMA, and forest, wetland, and floodplain shares all rise near WMA boundaries. Parcels within 1/4 mile of a WMA are roughly 20% more likely to fall on forest or wetland land cover than parcels beyond five miles, exactly the pattern expected if WMAs were systematically sited on marginal agricultural ground. Second, assessor under-reaction to recreation amenity: Arkansas county assessors value agricultural land primarily on soil quality, acreage, and access, with limited formal adjustment for proximity to public hunting lands. The 20% statutory assessment ratio and infrequent reappraisals further attenuate market signals. Third, a between-vs.-within-zone sign pattern: Model 1 (no zone fixed effects) shows a positive association between WMA proximity and values at the between-zone level, because zones with more WMAs (the Ozarks, near Northwest Arkansas) have higher average values; Model 2 (with deer-zone fixed effects) reveals the within-zone gradient, where WMAs are on the worst land within each region. The move from Model 1 to Model 2 is therefore a between-to-within contrast, not evidence of a causal amenity-destroying effect of WMA designation. Transaction prices, which internalize both assessor-visible and assessor-invisible amenities, should produce a positive gradient in a properly specified sample.

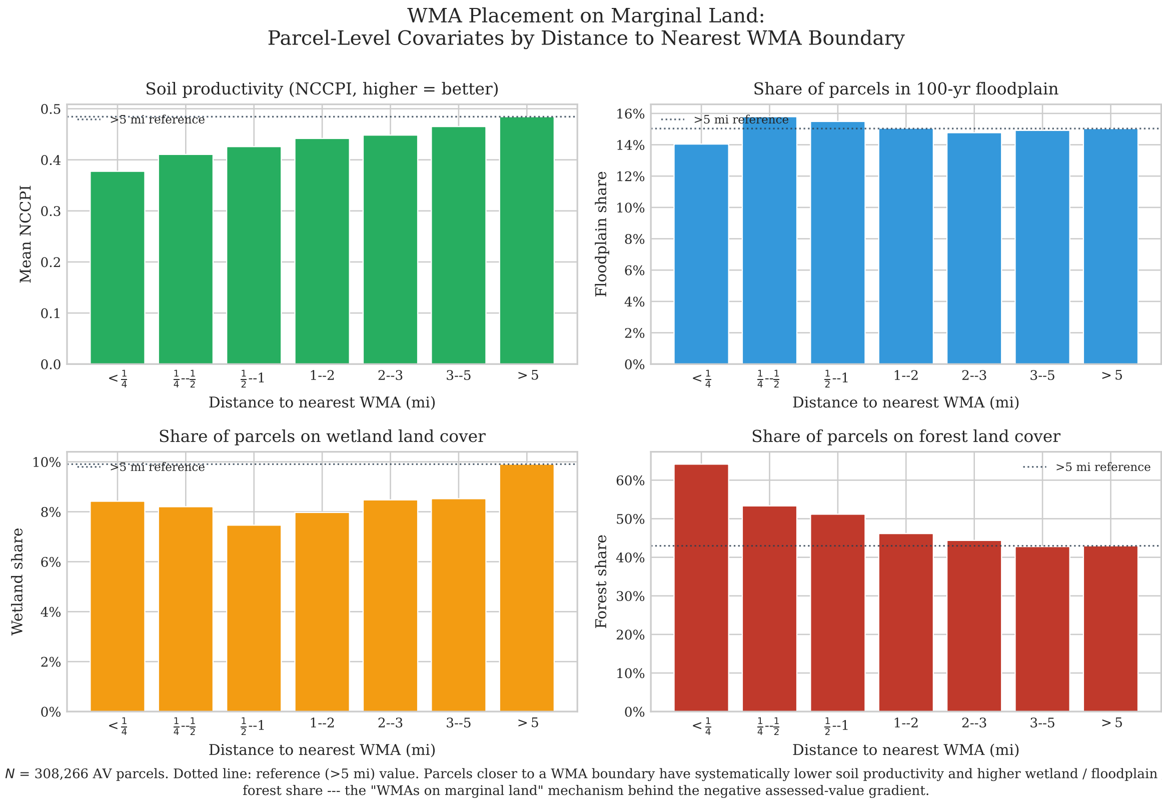

Figure 12: WMA placement on marginal land, measured at the parcel level. Mean soil productivity (top-left, NCCPI) rises monotonically with distance from the nearest WMA boundary. Floodplain share (top-right), wetland share (bottom-left), and forest share (bottom-right) are all elevated near WMAs relative to the >5 mile reference. These patterns are the direct parcel-level signature of the placement-selection mechanism that drives the negative assessed-value gradient.

The CWD null result in this cross-section (-5.2%, $p = 0.33$) has a related explanation. CWD zone counties are concentrated in the Ozarks, where land values differ from non-CWD counties for reasons unrelated to the disease; the county-level CWD indicator lacks temporal variation in a single CAMA snapshot; and assessed values lag any market perception of CWD as a hunting-experience threat. None of the three CWD specifications tested (binary zone, ln(1+positives), seasons-in-zone) is individually significant; across all three, the WMA coefficient is unchanged to four decimal places. The proper tool is a staggered difference-in-differences design on transaction data exploiting the phased zone expansion (Section 9).

8.3 Comparison to Literature

The findings are consistent with the existing literature when the cross-sectional identification limitation is accounted for. The closest parcel-level comparison is Casola et al.

[2022], who finds spatially heterogeneous WMA proximity effects on North Carolina residential properties—positive at moderate distances, negative at the boundary—suggesting that WMA placement confounding is a general phenomenon rather than an Arkansas artifact. Pope and Goodwin [1984] estimates that hunting rights add 10–25% to farmland values, while lease-rate studies [Hussain et al., 2013, Munn and Hussain, 2010] imply capitalization rates of 7–8% for hunting-lease income. These market-based estimates suggest the true positive amenity in transaction prices will be in the low single-digit percent range per mile of distance—well within the detection power of the validated pipeline. The CWD null is consistent with Tanger et al. [2025], who find that CWD detection *on the property* reduces Tennessee and Mississippi hunting-lease rates by 22% but CWD on nearby properties has no significant effect; at the Hussain et al. [2013] capitalization rate, the implied sale-price effect is a few hundred dollars per acre, below the detection power of a cross-section. Gavin et al. [2019] document a 5.4% decline in Wisconsin permit demand after CWD detection, providing an order-of-magnitude benchmark for the effects a staggered DiD design on Arkansas transaction data should be able to identify.

9 Limitations and Next Steps

9.1 Limitations

This analysis faces several limitations that constrain causal interpretation and motivate the next phase of the research program.

Assessed values are not transaction prices. The dependent variable is assessed land value per acre from a CAMA snapshot, not a market transaction price. The 20% statutory assessment ratio, assessor smoothing, and infrequent reappraisals attenuate market signals and cannot capture dynamic responses to shocks such as CWD detection or WMA establishment. The negative WMA proximity gradient likely reflects assessor judgment rather than market willingness to pay; sign and magnitude may differ substantially in transaction prices.

Cross-sectional identification. A single CAMA snapshot provides no temporal variation to distinguish treatment effects from selection effects. The negative gradient could reflect a causal effect of WMA designation or the selection of low-value land for WMA designation; without before/after variation these cannot be separated.

WMA placement endogeneity. WMAs were established on marginal agricultural land—bottomland hardwoods, steep terrain, flood-prone areas—so nearby parcels mechanically share low-value characteristics. This is the fundamental identification challenge for cross-sectional hedonic studies of public-land effects.

Deer quality confounds. The zone-level B&C z-score captures the full vector of zone-level characteristics correlated with deer quality (physiographic region, forest composition, soil, climate, urban proximity), not hunting quality in isolation. The generated-regressor bootstrap in Section 6 quantifies the sampling error in z-score construction; the coefficient is not interpretable as a causal hunting-quality effect. Some county-season biodata cells also have few observations, introducing measurement error that zone-level aggregation only partially mitigates.

CWD underpowered. The county-level CWD zone indicator lacks temporal variation in the cross-section, and the 17 affected counties may not provide sufficient power to detect modest effects after conditioning on county-level controls. None of the three CWD specifications tested (binary zone, $\ln(1 + \text{positives})$, seasons-in-zone) is individually significant at conventional levels.

9.2 Next Steps

The proof-of-concept analysis presented here validates the spatial pipeline and identifies the specifications most likely to yield causal estimates once transaction data is acquired. Five next steps are prioritized.

Transaction data acquisition (critical path). The single most important step is acquiring rural land transaction data with sale prices and dates. Three sources are being pursued: (a) the Arkansas Assessment Coordination Division's statewide transfer database; (b) CoreLogic/ZTRAX, a commercial transaction database with extensive coverage; and (c) individual county assessors' recorded-sale records. The target sample is arms-length rural and agricultural transactions from 2010 to 2025, providing at least five years pre-CWD and nine years post-CWD.

Staggered difference-in-differences for CWD. This is the highest-priority design enabled by transaction data, exploiting plausibly exogenous treatment assignment driven by disease biology rather than policy choice. With transaction dates, a DiD framework can use the staggered CWD zone expansion (10 counties in 2016, 15 in 2018, 17 in 2021) as a natural experiment under the Callaway and Sant'Anna [2021] or Sun and Abraham [2021] frameworks for staggered adoption. Unlike WMA placement, CWD zone designation is driven by disease biology and occurs at known dates, providing plausibly exogenous treatment. The target specification is

$$\ln(\text{price}_{ict}) = \alpha_i + \tau_t + \sum_{e \in \{2016,2018,2021\}} \beta_e \cdot \mathbf{1}\{c \in \text{cohort } e\} \cdot \mathbf{1}\{t \geq e\} + \mathbf{X}'_{ict}\boldsymbol{\gamma} + \epsilon_{ict}, \quad (3)$$

where i indexes parcels, c counties, and t transaction years. Parcel fixed effects α_i absorb time-invariant placement endogeneity—the central identification threat in the current cross-section—and year fixed effects τ_t absorb statewide agricultural-land trends. The three cohort $\times$ post dummies identify the dynamic price response by treatment timing; Equation (3) will be estimated via the Callaway and Sant'Anna [2021] and Sun and Abraham [2021] event-cohort estimators to handle treatment-effect heterogeneity that biases the naive two-way fixed-effect estimator. Pre-trend tests on a 2010–2015 sample window provide the standard parallel-trends validation. Figure 13 visualizes the resulting cohort-by-season treatment structure.

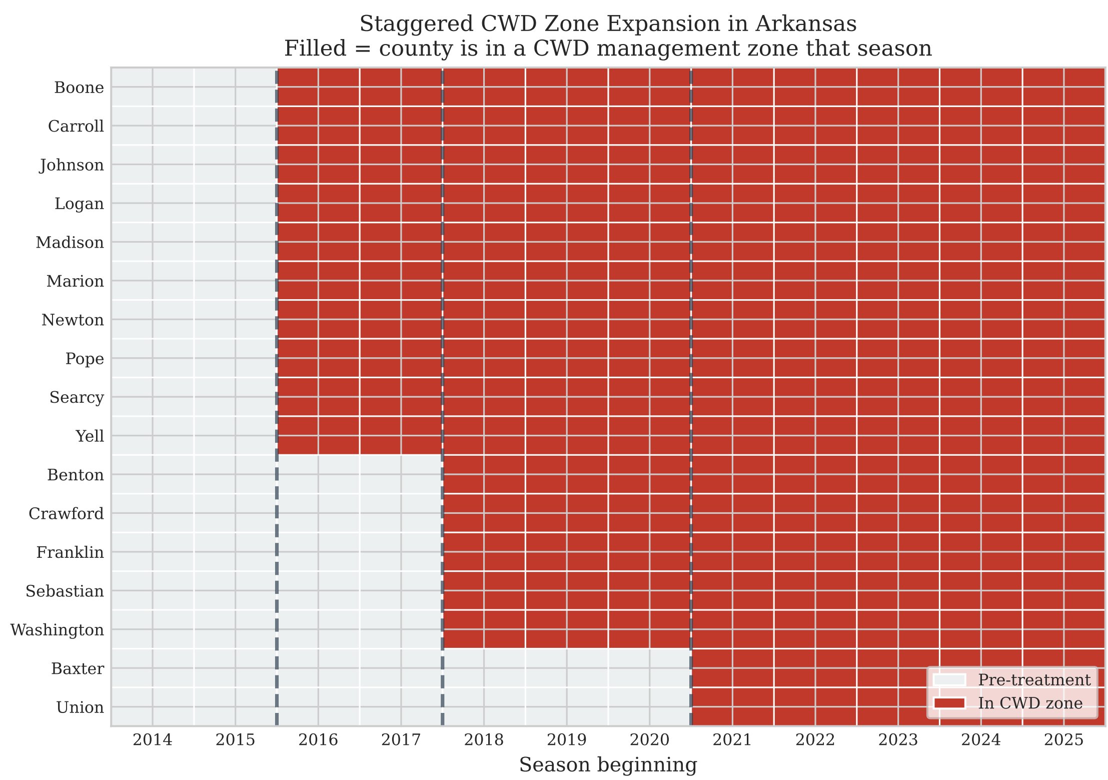

Figure 13: Staggered CWD zone expansion in Arkansas, 2014–2025. Each row is a CWD-zone county; each column a season. Filled cells indicate the county is in a CWD management zone that season. Dashed vertical lines mark the 2016, 2018, and 2021 cohort onsets. This three-cohort staggered structure is what identifies the Callaway and Sant'Anna [2021] or Sun and Abraham [2021] event-cohort estimators once transaction data are available.

WMA establishment dates. Compiling historical WMA establishment and expansion dates enables a second DiD analysis: treatment is WMA creation, outcome is the change in nearby land prices before and after. AGFC historical records and web-scraped sources have already partially compiled these dates. This design addresses placement endogeneity directly by comparing the same parcels before and after WMA creation.

Hunting regulation history. Zone-year bag limits, season lengths, and antler restrictions provide additional policy variation for instrumental-variables estimation or as separate treatments. A bag-limit increase provides identifying variation separate from WMA proximity or deer quality.

Spatial econometric models. The current analysis uses Conley HAC standard errors to address spatial correlation but does not estimate spatial-lag or spatial-error models (SAR, SEM). Implementing these on 308,220 observations is computationally feasible with sparse weight matrices and would improve efficiency if the data-generating process includes spatial spillovers.

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Appendices

A Full Regression Output

Table 11 presents the complete regression output for the first six model specifications (M1–M6). Table 12 continues with the remaining six specifications (M7–M3-AV). Parcel-level control coefficients, fixed effect indicators, sample sizes, and goodness-of-fit measures are reported for each specification.

Table 11: Full Regression Output: Models 1–3T

	M1 (County)	M4 (County)	M2 (Cty+Zone)	M3 (Bins)	M9 (Type Int.)	M6 (Z-score)
WMA Distance Variables						
dist_to_wma_km	−0.002***	−0.002***	+0.003*			+0.003
	(0.000)	(0.000)	(0.001)			(0.002)
inside_wma	−0.166***		−0.109**			−0.102*
	(0.011)		(0.039)			(0.045)
<1/4 mile				−0.175***	−0.174***	
				(0.026)	(0.027)	
1/4–1/2 mile				−0.110***	−0.109***	
				(0.023)	(0.024)	
1/2–1 mile				−0.082***	−0.081***	
				(0.020)	(0.021)	
1–2 miles				−0.060**	−0.059**	
				(0.020)	(0.021)	
2–5 miles				−0.023	−0.023	
				(0.016)	(0.017)	
Deer Quality						
mean_bc_zscore						+1.164***
						(0.271)
Parcel Controls						
ln(acres)	Yes	Yes	Yes	Yes	Yes	Yes
is_forest	Yes	Yes	Yes	Yes	Yes	Yes
is_wetland	Yes	Yes	Yes	Yes	Yes	Yes
in_100yr_flood	Yes	Yes	Yes	Yes	Yes	Yes
ln(dist paved)	Yes	Yes	Yes	Yes	Yes	Yes
ln(dist urban)	Yes	Yes	Yes	Yes	Yes	Yes
ln(dist water)	Yes	Yes	Yes	Yes	Yes	Yes
in_natl_forest	Yes	Yes	Yes	Yes	Yes	Yes

Continued on next page

	M1	M4	M2	M3	M9	M6
ln(dist federal)	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Deer Zone FE	No	No	Yes	Yes	Yes	No
Model Statistics						
R^2	0.520	0.519	0.572	0.573	0.573	0.533
N	476,874	476,874	476,853	476,853	476,853	476,853

Table 12: Full Regression Output: Models M7, M8, M5, M5b, M2-AV, M3-AV

	M7 (Interact.)	M8 (CWD Int.)	M5 (Cty Ctrl)	M5b (Cty Ctrl)	M2-AV (AV Only)	M3-AV (AV Only)
WMA Distance Variables						
dist_to_wma_km	+0.003		+0.002		+0.003*	
	(0.002)		(0.001)		(0.001)	
inside_wma	−0.101*		−0.111*		−0.236***	
	(0.045)		(0.049)		(0.029)	
dist × zscore	+0.016					
	(0.010)					
<1/4 mile		−0.173***		−0.168***		−0.178***
		(0.027)		(0.028)		(0.028)
1/4–1/2 mile		−0.108***		−0.099***		−0.113***
		(0.024)		(0.026)		(0.026)
1/2–1 mile		−0.081***		−0.076***		−0.078***
		(0.021)		(0.021)		(0.020)
1–2 miles		−0.059**		−0.050*		−0.053**
		(0.020)		(0.020)		(0.020)
2–5 miles		−0.022		−0.009		−0.023
		(0.016)		(0.016)		(0.016)
Deer Quality						
mean_bc_zscore	+1.147***					
	(0.275)					
CWD Variables						
in_cwd_zone			−0.052	−0.048		
			(0.053)	(0.052)		
CWD × bins		Joint $F(5, 72)$=0.26				
		p=0.93				

Continued on next page

	M7	M8	M5	M5b	M2-AV	M3-AV
County-Level Controls						
crp_pct			−0.053*	−0.051*		
mean_nccpi			+0.982*	+0.975*		
ln_population			+0.125***	+0.123***		
elevation_km			−0.059	−0.055		
fayetteville_shale			+0.018	+0.016		
ln_med_income			−0.234	−0.228		
pct_prime_farm			+0.005*	+0.005*		
Parcel Controls						
All parcel controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects						
County FE	Yes	Yes	No	No	Yes	Yes
Deer Zone FE	No	Yes	Yes	Yes	Yes	Yes
County Controls	No	No	Yes	Yes	No	No
Model Statistics						
R^2	0.533	0.573	0.555	0.556	0.587	0.587
N	476,853	476,853	476,853	476,853	309,430	309,430

Notes: Clustered standard errors (county) in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Reference category for distance bins: >5 miles. "Yes" indicates variable included but coefficient not shown for brevity. M9 type interaction F-test: $F(15, 72) = 0.47$, $p = 0.95$. Sample sizes differ between M1 (476,874) and M2+ (476,853) due to singleton zone drops.

B Variable Definitions and Deer Quality Methodology

Boone & Crockett Age-Class Standardization

Figure 14 displays the distribution of Boone & Crockett gross scores by age class in the AGFC biodata. Older bucks produce systematically higher scores, motivating the within-age-class z-score standardization described in Section 3. The 2013–14 season (excluded from the reference distribution) exhibited anomalously low derived B&C scores due to a scoring formula error; raw antler measurements were unaffected.

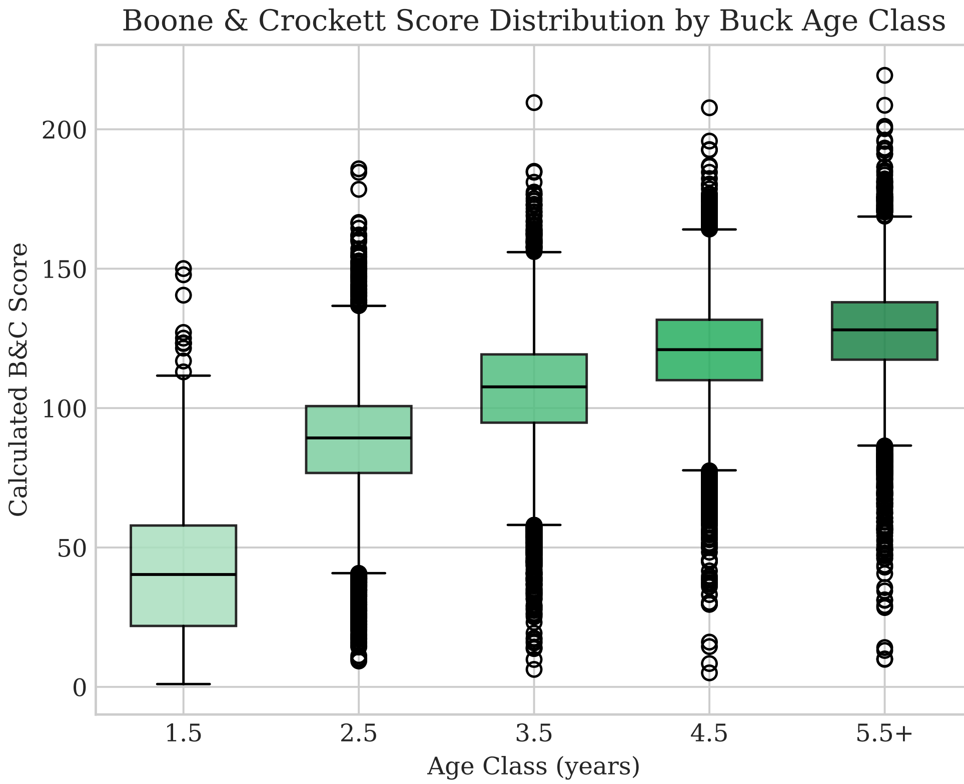

Figure 14: Distribution of Boone & Crockett gross scores by age class. Age-class normalization is essential because older bucks produce systematically higher scores, so a naive comparison of raw zone-level scores would confound age composition with trophy quality.

Full Variable Dictionary

Table 13: Variable Definitions, Sources, and Measurement Level

Variable	Definition	Source	Level
Dependent Variable			
ln_land_value_acre	Natural log of assessed land value per acre	AR GIS CAMA	Parcel
WMA Variables			
dist_to_wma_km	Euclidean distance (km) from parcel centroid to nearest WMA boundary	AGFC boundaries	Parcel

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Variable	Definition	Source	Level
wma_dist_bin	Categorical: <1/4mi, 1/4–1/2mi, 1/2–1mi, 1–2mi, 2–5mi, >5mi	Derived	Parcel
inside_wma_flag	Indicator: parcel centroid within WMA boundary	AGFC boundaries	Parcel
nearest_wma_type	Categorical WMA type (Ozark, Delta, Ouachita, River Valley)	AGFC + ecoregion	Parcel
Parcel Controls			
ln_acres	Natural log of parcel acreage	AR GIS CAMA	Parcel
is_forest	Indicator: majority land cover is forest (NLCD 41–43)	NLCD 2021	Parcel
is_wetland	Indicator: majority land cover is wetland (NLCD 90, 95)	NLCD 2021	Parcel
in_100yr_floodplain	Indicator: parcel in FEMA 100-year flood zone	FEMA NFHL	Parcel
ln_dist_paved_km	Log distance (km) to nearest paved road	Census TIGER	Parcel
ln_dist_ua_km	Log distance (km) to nearest Census Urban Area	Census 2020	Parcel
ln_dist_any_water_km	Log distance (km) to nearest water body or stream	NHD	Parcel
in_national_forest	Indicator: parcel within national forest boundary	PAD-US 4.1	Parcel
ln_dist_federal_km	Log distance (km) to nearest federal land	PAD-US 4.1	Parcel
County-Level Variables			
elevation_km	Mean county elevation in kilometers	USGS 3DEP	County
in_fayetteville_shale	Indicator: county overlaps Fayetteville Shale play	AOGC wells	County

Continued on next page

Variable	Definition	Source	Level
crp_pct_county_area	CRP enrolled acres as % of county area	NASS Census Ag	County
in_cwd_zone	Indicator: county in CWD management zone (2024–25)	AGFC reports	County
mean_nccpi	National Commodity Crop Productivity Index (0–1)	SSURGO	County
ln_population	Log of county population	ACS 5-year	County
ln_median_income	Log of county median household income	ACS 5-year	County
pct_prime_farmland	Percent of county area classified as prime farmland	SSURGO	County
Deer Quality Variable			
mean_bc_zscore	Mean age-normalized B&C z-score for the deer zone	AGFC biodata	Zone

C CWD Zone Panel

Table 14 summarizes the CWD management zone evolution in Arkansas from the 2016–17 through 2024–25 seasons, showing which counties entered the zone in each phase and their cumulative positive detections through FY25.

Table 14: CWD Management Zone: County Entry and Cumulative Detections

County	Season Entered	Tier (2024–25)	Cumulative Positives
Phase 1: Initial Zone (2016–17)			
Newton	2016–17	1	970
Boone	2016–17	1	306
Carroll	2016–17	1	221
Madison	2016–17	1	168
Searcy	2016–17	1	146
Johnson	2016–17	1	56
Marion	2016–17	1	19
Pope	2016–17	2	16

Continued on next page

County	Season Entered	Tier (2024–25)	Cumulative Positives
Logan	2016–17	2	11
Yell	2016–17	2	0
Phase 2: First Expansion (2018–19)			
Washington	2018–19	2	44
Benton	2018–19	2	22
Crawford	2018–19	2	7
Franklin	2018–19	2	7
Sebastian	2018–19	2	9
Phase 3: Second Expansion (2021–22)			
Baxter	2021–22	2	1
Union	2021–22	2	2
Total (17 counties)			**2,005**
Counties with detections outside CWD zone			
Randolph	Not in zone	—	6
Van Buren	Not in zone	—	7
Stone	Not in zone	—	5
Scott	Not in zone	—	4
Independence	Not in zone	—	4
Conway	Not in zone	—	2
Cleburne	Not in zone	—	2
Craighead	Not in zone	—	1
Statewide Total			**2,036**

Notes: Tier assignments reflect the 2024–25 season classification. Tier 1 (core) counties have sustained high CWD prevalence and are subject to mandatory testing. Tier 2 (peripheral) counties are in the buffer zone with voluntary testing encouraged. Cumulative positives are through FY25. The two-tier system was introduced in the 2021–22 season, reclassifying some original zone counties from untiered to Tier 1 or Tier 2. Union County (Phase 3) is geographically distant from the Ozark epicenter, reflecting a separate detection event in southern Arkansas.

D Deer Quality Split-Sample Analysis (Physiographic Heterogeneity)

We test whether the WMA proximity gradient differs by zone-level deer quality by splitting the sample into high-quality zones (mean z-score > 0, $N = 196{,}977$) and low-quality zones (mean z-score ≤ 0, $N = 279{,}876$). Because zone-level deer quality co-varies strongly with physiographic region—high-quality zones concentrate in the Ozark Plateau and White River corridor, low-quality zones in the Mississippi Delta—this split is best interpreted as testing for physiographic heterogeneity rather than a hunting-quality treatment effect.

Model 7, which adds an interaction between continuous WMA distance and the B&C z-score, produces $\hat{\beta}_3 = +0.016$ ($p = 0.12$)—directionally consistent with a steeper proximity gradient in high-quality zones but not conventionally significant. The split-sample estimates in Table 15 are more striking: the gradient is three to four times steeper in high-quality zones.

Table 15: Split-Sample: WMA Proximity Gradient by Deer Quality

Distance Bin	High Quality ($z > 0$)	Low Quality ($z \leq 0$)
<1/4 mile	−0.309	−0.080*
1/4–1/2 mile	−0.200	−0.038
1/2–1 mile	−0.141	−0.030
1–2 miles	−0.115	−0.011
2–5 miles	−0.037	−0.006
N	196,977	279,876
R^2	0.476	0.586

Both models include county FE, zone FE, and parcel controls.

Standard errors for the high-quality subsample could not be reliably estimated with county-clustered inference due to a reduced number of effective clusters (54 counties). Point estimates are reported without significance indicators; the magnitude difference is suggestive and should be interpreted as physiographic heterogeneity.

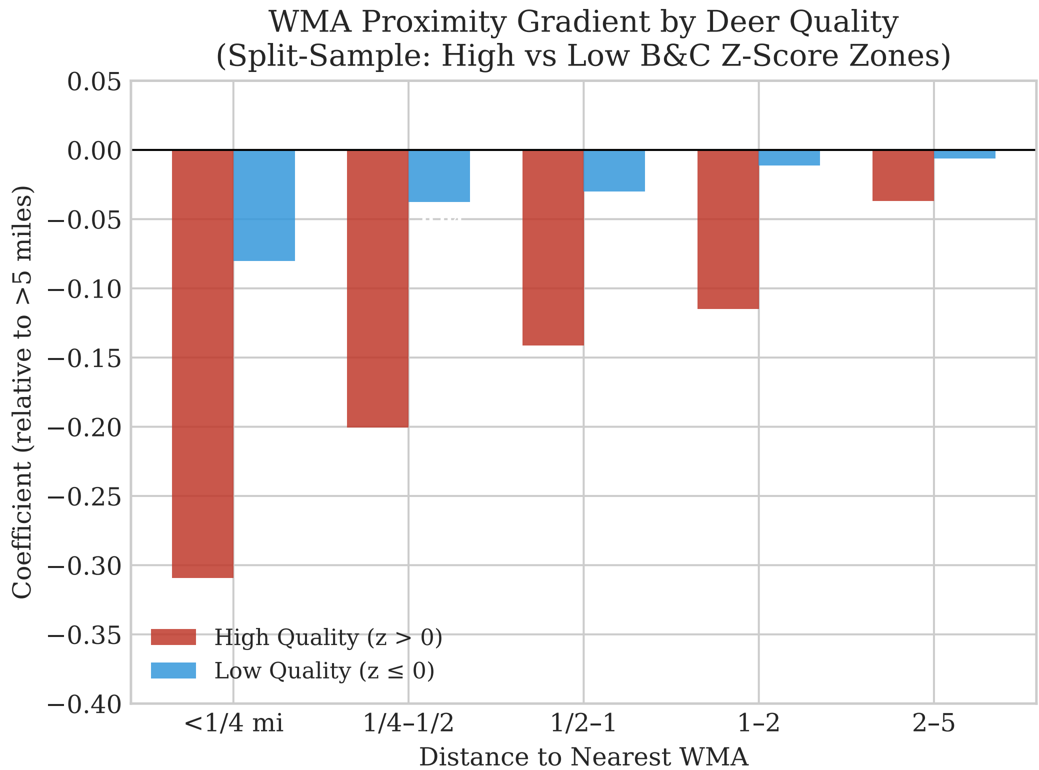

Figure 15: WMA proximity gradient by deer-quality group. High-quality zones (solid line) exhibit a dramatically steeper gradient than low-quality zones (dashed line); the <1/4 mile discount is nearly four times larger.

The steeper gradient in high-quality zones reflects land-quality sorting driven by physiography rather than differential hunting-amenity capitalization. High-quality zones correspond to the Ozark Plateau, where rugged terrain creates sharp contrasts between WMA-adjacent land (steep, rocky, forested) and the best agricultural parcels in the zone (valley bottoms with deeper soils). In the flat Mississippi Delta, WMA-adjacent land is physiographically similar to surrounding farmland, producing a shallow gradient. The lower R^2 in the high-quality subsample (0.476 vs. 0.586) is consistent with this interpretation: if the steep gradient reflected a genuine amenity effect, the model should fit better when the amenity is more salient; the lower R^2 instead suggests greater unexplained topographic heterogeneity in the Ozarks sample that the parcel-level controls imperfectly capture.

E Harvest Intensity and Hunter Effort

Figure 16 displays the distribution of deer harvest by day of week, serving as a proxy for hunter effort patterns.

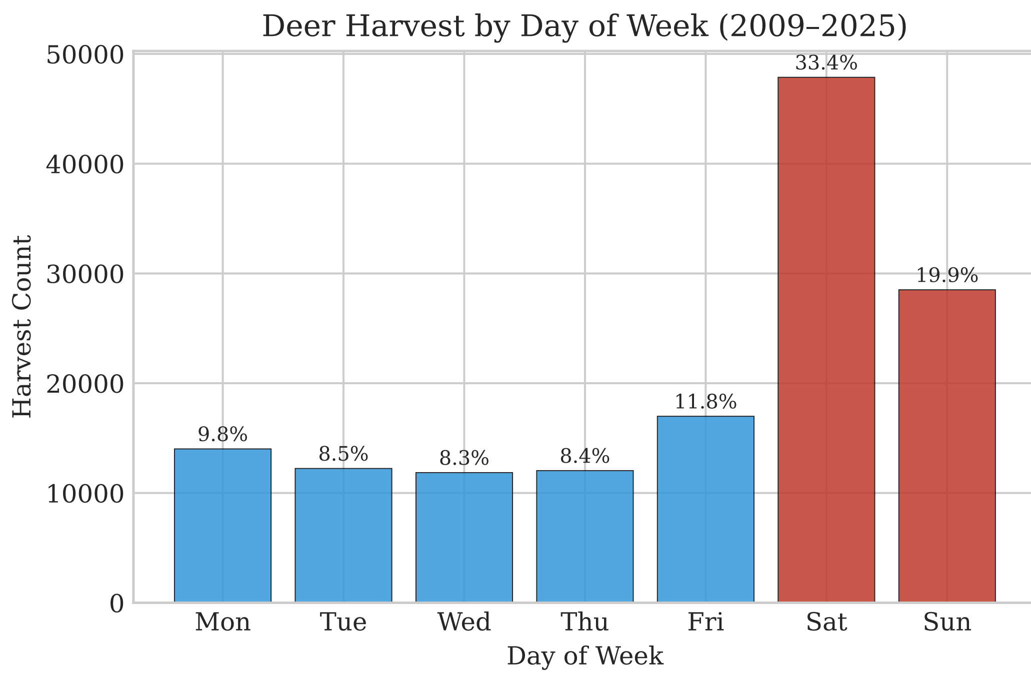

Figure 16: Deer harvest by day of week. Saturday dominance reflects weekend hunting patterns, with modern gun season accounting for the plurality of harvest. The day-of-week pattern is consistent across zones and seasons.

Saturday accounts for the largest share of weekly harvest, consistent with the expectation that recreational hunters concentrate effort on weekends. Modern gun season contributes the plurality of total harvest. The day-of-week pattern is remarkably consistent across zones and seasons, suggesting that hunter effort allocation is driven by work schedules and season structure rather than local deer quality or WMA characteristics.

Harvest intensity serves as an indirect measure of hunting pressure. Zones with higher harvest per unit area may experience greater hunting-related land demand, though this relationship is confounded by population density and access. Future work with transaction data and spatially resolved hunting participation data could exploit this variation more directly.