



# Cultivation and dynamic cropping processes impart land-cover heterogeneity within agroecosystems: a metrics-based case study in the Yazoo-Mississippi Delta (USA)

Lucas J. Heintzman · Nancy E. McIntyre ·  
Eddy J. Langendoen · Quentin D. Read

Received: 20 June 2023 / Accepted: 19 October 2023 / Published online: 14 February 2024  
© The Author(s) 2024

## Abstract

**Context** Cultivation and crop rotation, influenced by federal policy, prices, and precipitation, are significant sources of land-cover heterogeneity. Characterization of heterogeneity is required to identify areas and trends of stability or change.

**Objectives** We analyzed a land-cover time series within a prominent agroecosystem in the US, the Yazoo-Mississippi Delta (the Delta), as a case study

of which metrics capture dynamics of landscape composition, configuration, connectivity, and context.

**Methods** An assessment of land cover- from 2008 to 2021- was conducted and analyzed for potential differences among three Farm Bill eras. Twelve out of 23 metrics (including three new ones presented herein) examined were useful in characterizing land-cover heterogeneity.

**Results** Although there was no increase in cultivated land, > 72% of the Delta experienced changes in land-cover type, and ~3% of the Delta was stable monoculture. Configurational metrics varied across years for soybeans, cotton, and rice, indicating prevalence of field-level changes in composition; connectivity metrics revealed isolation of upland forest and rice. The amount of corn was positively associated with the previous year's commodity prices and negatively with precipitation whereas soybean acreage was lower in high-precipitation years and more dependent on commodity prices. Farm Bill effects were mixed among categories, whereas CRP generally declined.

**Conclusions** The Delta experienced land-cover change with no net loss or gain of cultivated lands. Using 12 metrics that captured temporal shifts in spatial patterns, we characterized this agroecosystem as a shifting mosaic. Our approach may be useful for identifying areas of spatio-temporal heterogeneity or stability, with implications on resource management.

---

**Supplementary Information** The online version contains supplementary material available at <https://doi.org/10.1007/s10980-024-01797-0>.

---

L. J. Heintzman  
Water Quality and Ecology Research Unit, National Sedimentation Laboratory, United States Department of Agriculture-Agricultural Research Service, Oxford, MS 38655, USA  
e-mail: lucas.heintzman@usda.gov

N. E. McIntyre (✉)  
Department of Biological Sciences, Texas Tech University, Lubbock, TX 79409-3131, USA  
e-mail: nancy.mcintyre@ttu.edu

E. J. Langendoen  
Watershed Physical Processes Research Unit, National Sedimentation Laboratory, United States Department of Agriculture-Agricultural Research Service, Oxford, MS 38655, USA

Q. D. Read  
Department of Agriculture-Agricultural Research Service, Southeast Area, Raleigh, NC 27606, USA

**Keywords** Crop rotation · Land-cover change · Landscape metrics

## Introduction

Agroecosystems experience spatial and temporal land-cover heterogeneity (Goslee 2020; Jeanneret et al. 2021). Categorizing such heterogeneity is key to elucidating pattern-process relationships within agroecosystems (Tschardt et al. 2005; Hopfenmüller et al. 2014; Jeanneret et al. 2021). However, it is unclear which aspects of landscape pattern (composition, configuration, connectivity, or context) are most modified within agroecosystems. (Composition refers to what kinds of land-cover types are present, configuration is how patches of land-cover types are arranged, connectivity assesses potential isolation of land-cover patches of a given type, and context refers to the overall setting in terms of homogeneity/heterogeneity and stability/instability [persistence] over time.) These attributes are poorly understood because the spatial properties of agroecosystems are seldom measured (Fahrig et al. 2011; Hopfenmüller et al. 2014) or are not examined over time (Corry 2019; Coffin et al. 2021). Which aspect of landscape pattern change is most pertinent to support sustainable agriculture remains uncertain (Landis 2017; Tschardt et al. 2021).

In the US, one important driver of agricultural change is the Farm Bill, a blanket term for federal legislation enacted every 4–6 years (most recently in 2008, 2014, and 2018) that provides financial support to produce certain crops, which serves to stabilize commodity prices. Additionally, Farm Bills support programs covering nutrition assistance, conservation, and other topics (CRS 2023). Attempts to balance commodity supply and demand may occur through payments to farmers to make up the difference between production costs and low market prices, by promoting shifts to other crops, or by incentivizing removal of cropland from production (e.g., by putting it into a long-term conservation program, such as the Conservation Reserve Program [CRP]). Created in the 1985 Farm Bill, the CRP was designed to reduce soil erosion, control commodity overproduction, and provide wildlife habitat by establishing long-term leases that pay landowners to take marginal lands out of cultivation and plant perennial forms of land cover instead (Hohman and Halloum 2000). These policies illustrate how the Farm Bill may drive landscape patterns. However, farmers may respond to favorable short-term market conditions or to weather conditions (especially precipitation) on a time

scale finer than the 4–6-year Farm Bill spans. Thus, differences in Farm Bill policies, commodity prices, and precipitation may be manifested in different cropping systems and thus in landscape pattern, but this is not well-understood.

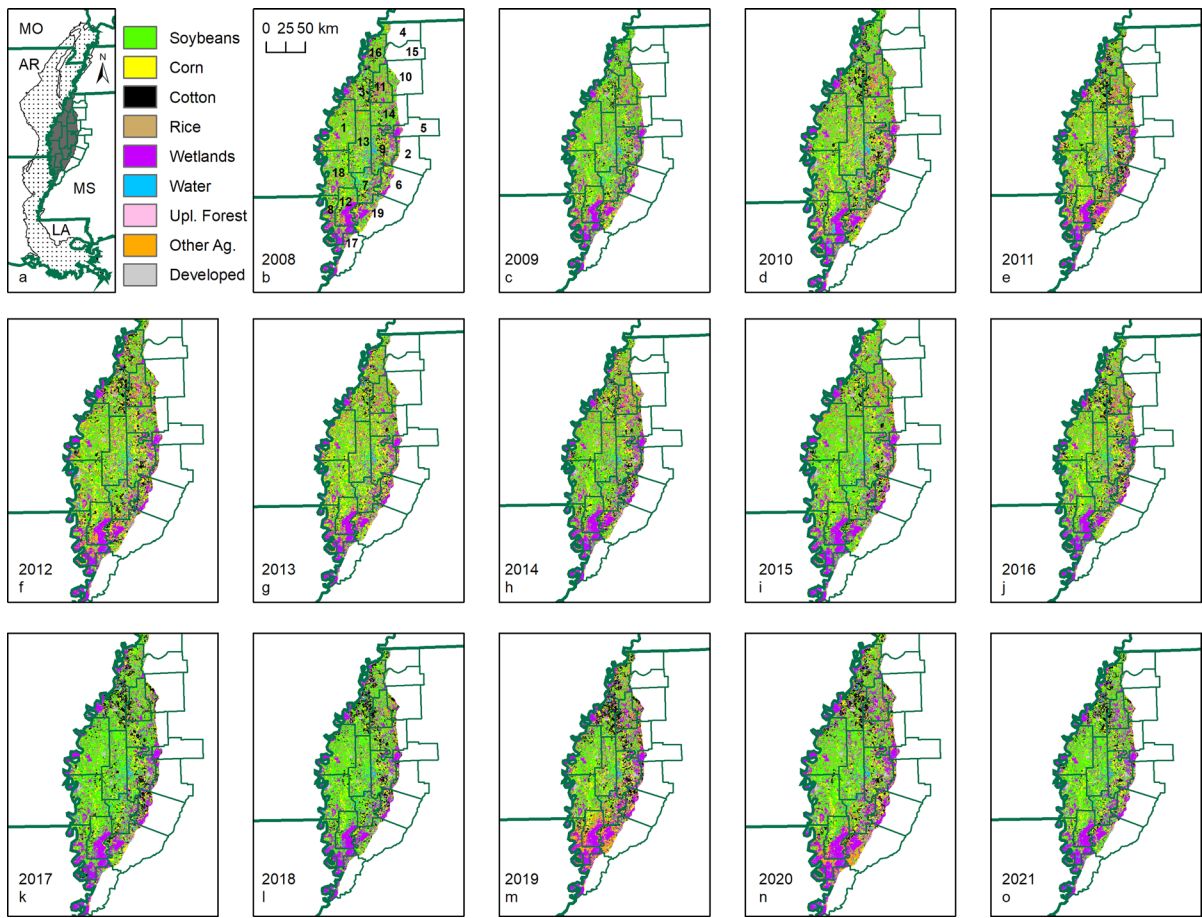
The Yazoo-Mississippi Delta (regionally known as “the Delta”) is a portion of the Mississippi Alluvial Plain that is intensively altered for soybean, corn, cotton, and rice production (Cobb 1992; Saikku 2005; Ambinakudige and Intsiful 2020; Yasarer et al. 2020) (Fig. 1a). Crop rotation is common, resulting in land-cover compositional changes (Ambinakudige and Intsiful 2020; Yasarer et al. 2020). Yearly rotations generally involve two crops (Bennett et al. 2012), generating routine fluctuations in landscape patterns (Corry 2018, 2019; Jeanneret et al. 2021). However, previous studies had limited detail about distributions and timings of land-cover changes. Thus, we lack knowledge about spatio-temporal heterogeneity, whether other structural properties (configuration, connectivity, and context) mirror changes in land-cover composition over time, and where the most stable (and the most dynamic) portions of the Delta occur. Moreover, we lack knowledge of how federal policies, commodity prices, or precipitation may drive these patterns, even though such knowledge informs regional management for sustainable agriculture (Faulkner et al. 2011; Parajuli et al. 2013; Risal and Parajuli 2019; Risal et al. 2020; Lo and Pringle III 2021).

Our objectives were to (1) quantify the spatio-temporal properties of land cover within the Delta. We sought to (2) identify areas of the Delta that were subject to the most (and least) landscape change through time. We (3) measured these changes via landscape metrics, which allowed us to (4) evaluate which metrics effectively characterized this agroecosystem and its dynamics. We (5) examined potential drivers of patterns (Farm Bill policies, commodity prices, precipitation). Lastly, we (6) discussed implications of these dynamic patterns of land-cover diversity for resource management.

## Methods

### Data

A summarized methodological workflow is in Supplementary Information (SI) Fig. S1. Land-cover data



**Fig. 1** a Map depicting the Mississippi Alluvial Plain (stippling) within the US states of Missouri (MO), Arkansas (AR), Louisiana (LA), and Mississippi (MS) (state boundaries as thick teal lines); the Delta portion (dark gray) occurs within 19 Mississippi counties (thin teal lines). **b–o**) Time series of land-cover changes from 2008–2021 for nine land-cover classes in

the 19 Mississippi counties that comprise the Delta: (1) Bolivar, (2) Carroll, (3) Coahoma, (4) Desoto, (5) Grenada, (6) Homes, (7) Humphreys, (8) Issaquena, (9) Leflore, (10) Panola, (11) Quitman, (12) Sharkey, (13) Sunflower, (14) Tallahatchie, (15) Tate, (16) Tunica, (17) Warren, (18) Washington, and (19) Yazoo

from 2008 to 2021 (hereafter, study period) for the 19 Mississippi counties of the Delta were downloaded from the United States Department of Agriculture National Agricultural Statistics Service’s Cropland Data Layer (USDA NASS CDL; <https://nassgeodata.gmu.edu/CropScape/>, Accessed June 2022; Boryan et al. 2011; Han et al. 2012). This land-cover data had a resolution of 30 m×30 m pixels (cells). Of the > 140 land-cover categories within the CDL, only 36–47 occurred within the Delta in any given year. These were reclassified in ArcMap 10.8.1 (Esri, Redlands, CA) to nine mutually exclusive land-cover categories (Table 1). Given the regional importance of soybeans, corn, cotton, and rice (Ambinakudige and

Intsiful 2020; Yasarer et al. 2020), those categories remained as-is from the CDL for analysis. All other crop types were less common (<5% in total, and typically <1%) and so were combined with fallow/idle croplands, hay fields, and pastures for livestock grazing into “other agriculture.” CRP lands occur in multiple habitat forms (e.g., grasslands, riparian, and/or timbered areas) and are not distinguishable from non-CRP regions in the CDL (to preserve landowner privacy). Thus, CRP of the Delta was likely distributed amongst the “other agriculture”, “wetlands”, and “upland forest” categories. Double cropping (the CDL’s designation for crop rotation within the same field in the same year) was rare ( $\leq 5.5\%$  per year, SI

**Table 1** Reclassification scheme we used, with the four primary crops of the Delta indicated

US Department of Agriculture's National Agricultural Statistics Service's Cropland Data Layer categories	Reclassified class name
Soybeans + Double Crops with Soybeans [primary crop]	Soybeans
Corn + Sweet Corn + Ornamental Corn + Double Crops with Corn [primary crop]	Corn
Cotton + Double Crops with Cotton [primary crop]	Cotton
Rice [primary crop]	Rice
Herbaceous Wetlands + Woody Wetlands + Wetlands	Wetlands
Open Water + Aquaculture	Water
Deciduous Forest + Evergreen Forest + and Mixed Forest	Upland Forest
All other non-developed categories + Double Crops among primary crops	"Other Agriculture"
Developed/ Open Space + Developed/ Low Intensity + Developed/ Medium Intensity + Developed/High Intensity	Developed

Table S1). When double cropping included only one of the four primary crops, it was assigned as the primary crop type. Double cropping including two-primary crops were especially rare (<0.5% per year, SI Table S1) and assigned to "other agriculture" because of the inability to assign it to an exclusive category.

The three most recent Farm Bills ("Food, Conservation, and Energy Act of 2008" [hereafter, FB Era I], "Agriculture Act of 2014" [FB Era II], and "Agriculture Improvement Act of 2018" [FB Era III]) were active during our focal span. We examined their potential influence on land-cover dynamics in the Delta by calculating average proportional landscape coverage of each land-cover class during each of their respective spans of time (2008–2013, 2014–2017, and 2018–2021). Those Farm Bill era averages of each class were then compared to the overall average of each class for the entire focal span. This allowed us to identify those Farm Bill eras that supported above-average and below-average land cover dynamics for each class, and to test specific predictions about the influence of each bill. For example, because the 2008 bill increased support for ethanol/biofuels through production of biomass crops, we anticipated seeing an increase in corn during FB Era I. The 2014 bill removed upland cotton as a covered commodity, but this was reinstated under protection of seed cotton by the Bipartisan Budget Act of 2018, so we expected to see a decline in FB Era II and recovery in cotton acreage in Era III. The 2018 bill included the Grassland Conservation Initiative to retain and expand pasture, so we expected to see an increase in pasture (part of "other agriculture," as it accounted for <5% of the

total landscape) in FB Era III. Finally, the 2008 Farm Bill capped CRP acreage at 32 million acres. The 2014 Farm Bill further capped CRP acreage down to 24 million acres; the 2018 Farm Bill increased the cap to 25 million acres. Thus, we expected to see declines in CRP prevalence on the landscape. Because CRP is not distinguishable in the CDL, we could not perform metric analyses on it. Instead, we report its prevalence at national and state levels (<https://www.ers.usda.gov/data-products/chart-gallery/gallery/chart-detail/?chartId=106658>; <https://www.fsa.usda.gov>).

To explore two other potential drivers of land cover, we examined growing-season precipitation and commodity prices for the four primary crops. Cumulative precipitation during the planting/growing season (March through June; hereafter, growing season) were obtained from the National Oceanic and Atmospheric Administration National Weather Service Greenville Area station (<https://www.weather.gov/wrh/climate?wfo=jan>). Commodity prices were obtained from the USDA Economic Research Service's Commodity Costs and Return database (<https://www.ers.usda.gov/data-products/commodity-costs-and-returns>, Accessed 1 May 2023).

### Metrics

Over 100 metrics quantify different aspects of landscape structure (Gustafson 1998; Frazier and Kedron 2017), with extensive attempts to identify the most parsimonious set needed to capture landscape heterogeneity (Li and Reynolds 1994; Riitters et al. 1995; Cushman et al. 2008). Emergent consensus indicated

that landscapes are typically too complex and diverse for only a few metrics to be universally recommended, but “fishing expeditions” for informative metrics are discouraged (Gustafson 2019). Therefore, we deliberately chose 20 metrics to describe the structure of the Delta in terms of composition, configuration, and connectivity changes (Table 2). These metrics examined patterns at two scales: within individual land-cover classes and the overall landscape. Metrics were calculated in Fragstats 4.2.1 (<https://www.fragstats.org>) using the 8-cell rule to designate patches of a given land-cover type. Use of this rule minimized the influence of any misclassification errors that were present in the CDL (Boryan et al. 2011) and statistical artifacts associated with the modifiable areal unit problem (Wickham and Ritters 1995; Jelinski and Wu 1996; Wu et al. 2000). These metrics were examined with respect to their ability to characterize the Delta in terms of the diversity and amounts of land-cover types present in each year, land-cover patch characteristics such as shape, and how land-cover types were spatially arranged (e.g., in larger, contiguous patches vs. in smaller, dispersed patches). We chose a small subset of metrics that are readily interpretable and further narrowed the subset down to ones that exhibited trends in change over time (as opposed to stasis or to fluctuations without a clear pattern).

Additionally, we developed three new landscape-scaled metrics of per-pixel land-cover richness, land-cover class change frequency, and land-cover class majority (Table 2) because there were no existing metrics to explicitly assess landscape context (that is, the overall setting in terms of homogeneity/heterogeneity in space and persistence over time). Land-cover richness was defined as the number of land-cover categories that occurred at a pixel during the study period. Land-cover class change frequency was defined as the count of land-cover category changes that occurred at a pixel on a year-to-year basis during the study period. Lastly, land-cover class majority was determined by tallying the most numerically prevalent land-cover type at each pixel; this allowed us to identify areas with similar land-use legacies, which may be informative of shared agroecological relationships therein (e.g., agrochemical applications). These contextual metrics allowed us to quantitatively describe transitions in land-cover richness over time (as well as the converse, persistence); we considered these metrics to inform a foundational

understanding of this underrepresented aspect of landscape heterogeneity (Pontius et al. 2004).

## Analyses

We plotted each of our 20 compositional, configurational, and connectivity metrics for each year to examine trends during our study period. We quantified, on a per-pixel basis, each of our contextual metrics for the same period. Contextual metrics were then mapped to identify portions of the Delta characterized by land-cover diversity or monoculture, and areas with stability or instability in land-cover type across years. In identifying areas of heterogeneity/homogeneity and stability/instability (i.e., context), we quantified the number of land-cover transitions experienced by each pixel over the study period. We examined (1) all transitions among land-cover classes, (2) transitions between consecutive cultivated land-cover classes, (3) transitions between consecutive non-cultivated land-cover types, and (4) transitions between consecutive cultivated and non-cultivated land-cover classes. Calculation of these transition dynamics was coded in Python via a Jupyter Notebook using the open-source scientific data analysis and computing packages pandas (<https://pandas.pydata.org/>) and NumPy (<https://numpy.org/>) (SI Document 1). The data were then converted into polygon features, which we refer to as “trajectories” because they contained information on the sequential nature of land-cover change, and we could quantify where those sequential changes had occurred. This enabled us to determine the proportional occurrence and area of those trajectories that contained evidence of sequential crop rotation. We examined sequential field rotation occurrence at three levels of intensity: at least once, at least half of our 13-year study period (i.e., at least seven times), and continuous. We then summarized those relationships by land cover. As an example: for the 1-land-cover class richness category, 9 trajectories were identified. These 9 trajectories represent portions of the Delta that only experienced a single type of land cover during the study period; we refer to this group of 9 trajectories collectively as “land-cover class core areas.” These analyses allowed us to ascribe patterns within the trajectories to processes such as crop rotation, urbanization, or flooding.

To examine the influence of potential drivers on landscape patterns, we first derived comparisons

**Table 2** Overview of metrics used to quantify landscape structure in the Yazoo-Mississippi Delta, 2008–2021

Principle landscape property considered	Metric name (abbreviation)	Scale(s)	Ecological interpretation
Composition	Percentage of landscape coverage (PLAND)	C, L	Commonness or rarity of land-cover types
Composition	Largest patch index (LPI)	C, L	Percentage of landscape covered by monoculture patches
Configuration	Number of patches (NP)	C, L	Distribution of land-cover types
Configuration	Mean patch area (AREA_MN)	C, L	Average size of patches and assay of monoculture
Configuration	Area-weighted mean patch area (AREA_AM)	C, L	Average size of patches and assay of monoculture, weighted by land-cover abundance
Configuration	Coefficient of variation of patch area (AREA_CV)	C, L	Distribution of variability in mean patch size
Connectivity	Mean Euclidean nearest-neighbor distance (ENN_MN)	C, L	Average patch isolation
Connectivity	Mean contiguity index (CONTIG_MN)	C, L	Average land-cover connectedness (LaGro 1991)
Connectivity	Contagion (CONTAG)	L	Dispersion of land-cover classes (Li and Reynolds 1993; Riitters et al. 1996)
Context	Land-cover Richness	L	Spatial heterogeneity
Context	Land-cover Change Frequency	L	Land-cover transitions
Context	Land-cover Class Majority	L	Land-cover stability
Composition	Patch richness (PR)*	L	Diversity of patch types
Configuration	Patch density (PD)*	C, L	Concentration of a given land-cover type
Configuration	Edge density (ED)*	C, L	Amount of patch edges
Configuration	Landscape shape index (LSI)*	C, L	Land-cover aggregation (Patton 1975)
Configuration	Mean shape index (SHAPE_MN)*	C, L	Average land-cover patch compactness (Patton 1975)
Configuration	Mean perimeter-area ratio (PARA_MN)*	C, L	Average patch shape
Configuration	Perimeter-area fractal dimension (PAFRAC)*	C, L	Scale-independent patch shape
Configuration	Interspersion and juxtaposition index (IJI)*	C, L	Patch edge similarity
Configuration	Proportion of like adjacencies (PLADJ)*	C, L	Land-cover interspersion
Configuration	Division index (DIVISION)*	C, L	Land-cover subdivision (Jaeger 2000)
Configuration	Modified Simpson's evenness index (MSIEI)*	L	Evenness of patch types

Scale(s) indicates whether the metric is calculated at the level of each land-cover class (C) or the landscape as a whole (L). Metrics indicated with \* did not exhibit marked variation over time (see SI Figs. S2-S12) and were not retained for analysis

from the compositional metric PLAND over three Farm Bill eras (periods of time spanning each bill). Additionally, we tallied total CRP acreage in Mississippi for the years 2008, 2012, 2014, 2018, and 2021. Finally, to examine the influence of precipitation and commodity prices (Table 3) on fluctuations in the amount of each of the four primary crops, we used the *dynlm* package v0.3–6 (Zeileis 2019) in R v4.2.2 (R Core Team 2022) to conduct a dynamic linear model time series analysis. Data from 2007 to 2021 were used (2007 data were included to model possible lag effects); the variables were standardized with a z-transformation and plotted on an annual time scale. (Proportion of landscape of each land-cover is a simple and intuitive metric and is statistically correlated to many other metrics; we thus used the proportional land-cover metric as a representative proxy.) This analysis assessed the relationships between the proportion of landscape for each primary crop (log-transformed) and commodity price and precipitation (and their interactions). Six models were compared for each crop: models with 0 year lagged predictors (current year effect), 1 year lagged predictors

(previous year effect), and both 0 and 1 year lagged predictors. In each of these cases, models with and without a price by precipitation interaction terms were fit. The model with the lowest AIC score for each crop was retained. Analytical code is available from Ag Data Commons ([data.nal.usda.gov](http://data.nal.usda.gov); see also SI Document 1, which includes detailed AIC values).

## Results

### Landscape composition

The most land-cover diversity (and changes over time) occurred in the southern, eastern, and northern portions of the Delta (compare Figs. 1b–o). These areas exhibited high spatial and temporal heterogeneity with differing amounts of cotton and corn production by year. Rice production typically was concentrated in the western part of the Delta. Southern portions of the Delta were characterized by extensive wetlands.

**Table 3** Growing-season precipitation and commodity prices for our four primary crops for the years 2007–2021 (2007 data were included to model possible lag effects)

Year	Growing-Season Precipitation (Mar–Jun, in., Greenville, MS)	Soybeans Price (US dollars per bushel at harvest)	Corn Price (US dollars per bushel at harvest)	Cotton Price (US dollars per pound)	Rice Price (US dollars per hundredweight at harvest)
2007	8.17	7.95	3.27	0.57	10.26
2008	17.68	10.48	4.36	0.60	17.88
2009	18.46	9.30	3.59	0.59	14.49
2010	8.78	9.56	4.33	0.82	11.3
2011	10.20	11.94	5.73	0.96	14.77
2012	15.98	14.21	6.79	0.71	14.95
2013	13.82	13.28	4.61	0.82	16.81
2014	26.20	10.88	3.54	0.68	14.05
2015	15.04	8.97	3.66	0.61	13.09
2016	23.27	9.46	3.29	0.67	11.07
2017	12.85	9.28	3.25	0.69	12.15
2018	15.63	8.61	3.42	0.76	13.17
2019	34.17	8.61	3.83	0.61	12.74
2020	19.89	9.67	3.61	0.64	14.78
2021	17.93	11.98	5.04	0.88	14.91
Mean	17.85	10.45	4.22	0.72	14.01
Min	8.78	8.61	3.25	0.61	11.07
Max	34.17	14.21	6.79	0.96	17.88

*Min* minimum, *Max* maximum

Of 23 metrics examined, 12 exhibited informative trends over time: proportional coverage of a given land-cover type, largest patch index, number of patches, average patch size, the coefficient of variation of average patch size, area-weighted average patch size, average Euclidean nearest-neighbor distance, average land-cover contiguity, and overall landscape contagion, as well as our contextual metrics of land-cover richness, land-cover change frequency, and land-cover class majority. Soybeans were the most common land-cover type throughout the Delta across all years (Fig. 2a) and experienced the greatest fluctuations in coverage (~30–48%) (SI Table S2; Fig. 2b). Wetlands were consistently second in terms of dominance (~23–28%). Corn (~6–16%), cotton (~3–10%), and the “other agriculture” category (~2–13%) were the next most abundant forms of land cover, varying in relative dominance by year. Rice was the rarest of the four primary crops (~2–7%); the remaining three land-cover classes were also relatively rare (<5%), with minimal changes over time (Figs. 2a, b). The overall proportions of cultivated lands (soybeans, corn, cotton, rice, “other agriculture”) to non-cultivated lands (wetlands, water, upland forest, developed) were remarkably stable; departures of  $\pm 5\%$  only occurred twice over our study period (Fig. 2c). The Delta thus experienced no net loss of land-cover types into or out of agricultural production from 2008 to 2021. The largest patch index (Figs. 2d, e) indicated that the largest patch for each land-cover type generally stayed the same size over time, except for soybeans, which fluctuated greatly from year to year, with no overall increasing or decreasing trends (SI Table S3).

### Landscape configuration

Fluctuations in the number of patches were especially evident for soybeans, corn, and other agriculture. Upland forest and rice accounted for the smallest area and fewest patches (SI Table S4; Figs. 3a, b).

Average patch size was largest for the four primary crops and for wetlands (SI Table S5; Figs. 3c, d). Average patch size for rice was larger than for most other land-cover types, indicating that what little rice was present was spatially contiguous. The developed class displayed fluctuations in number of patches (Figs. 3a, b). The developed class also displayed limited variation in area-weighted mean patch size

(Figs. 4a, b) yet had greater variation in the coefficient of variation in mean patch size (Figs. 4c, d). The increasing trend in area-weighted mean patch size (SI Table S6; Figs. 4a, b) and stabilization of variation in patch size (SI Table S7; Figs. 4c, d) for soybeans signals coalescence of soybeans fields into larger patches. Similarly, when metrics of patch size (which indicate how large the contiguous clumps of a given land-cover type are) are examined in tandem with the number of patches of a given land-cover type, an increase in the number of patches and decrease in patch size over time for a given land-cover type can be an indicator of fragmentation. The trends of increasing patch size and a weaker one of a decrease in the number of patches of soybeans indicates that fewer but larger patches are coalescing, forming monocultures.

### Landscape connectivity

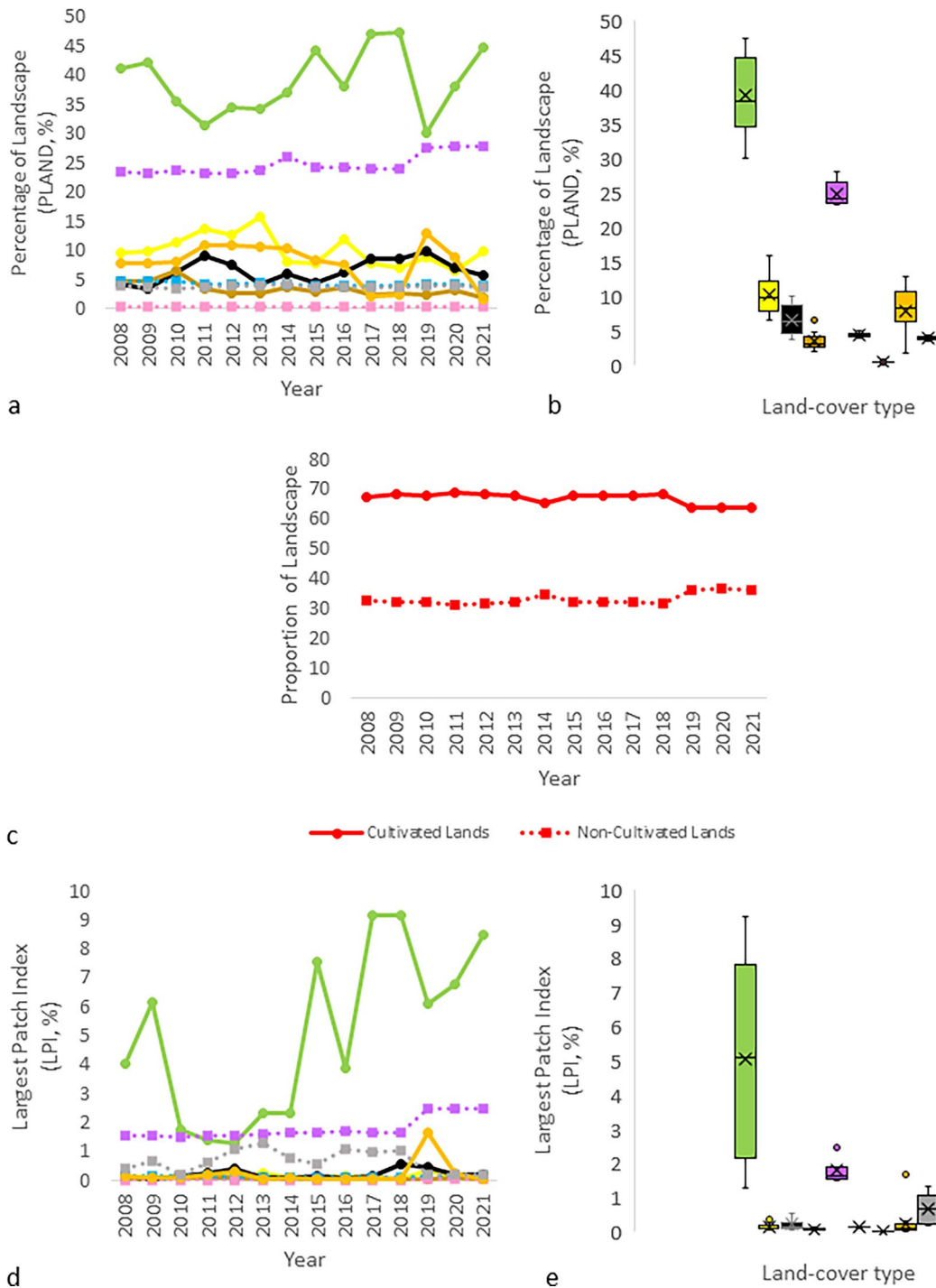
Mean Euclidean nearest-neighbor distances were consistently high for upland forest patches, signaling isolated patches separated by >500 m on average. Rice patches were also spatially well-separated, potentially reflecting presence of poorly draining soils that are preferentially utilized for rice production in the Delta. Rice patches generally became more isolated over time (SI Table S8; Fig. 5a and b). The lowest nearest-neighbor distances of the nine land-cover types occurred for developed areas, soybeans, and wetlands, presumably from different mechanisms.

The mean contiguity index (Figs. 5c, d), where larger index values indicate the presence of more contiguous patches of a given land-cover type (LaGro 1991), reinforced the observation that wetland patches were relatively contiguous and stable (SI Table S9). Peaks seen for cotton and rice in some years correspond to peaks in average patch size for those land-cover types (Figs. 5c, d). When examined in conjunction with the proportion of landscape covered and patch size, these peaks indicate changes in landscape patterning. Specifically, despite a doubling of cotton area between 2008 and 2017, cotton typically existed in relatively small, dispersed patches; only in 2017 was there a coalescence of cotton patches to form larger, monocultural areas. Similarly, rice patches became increasingly contiguous despite an overall decrease in proportional coverage of this crop type. Overall landscape contagion was intermediate



### COMPOSITION METRICS

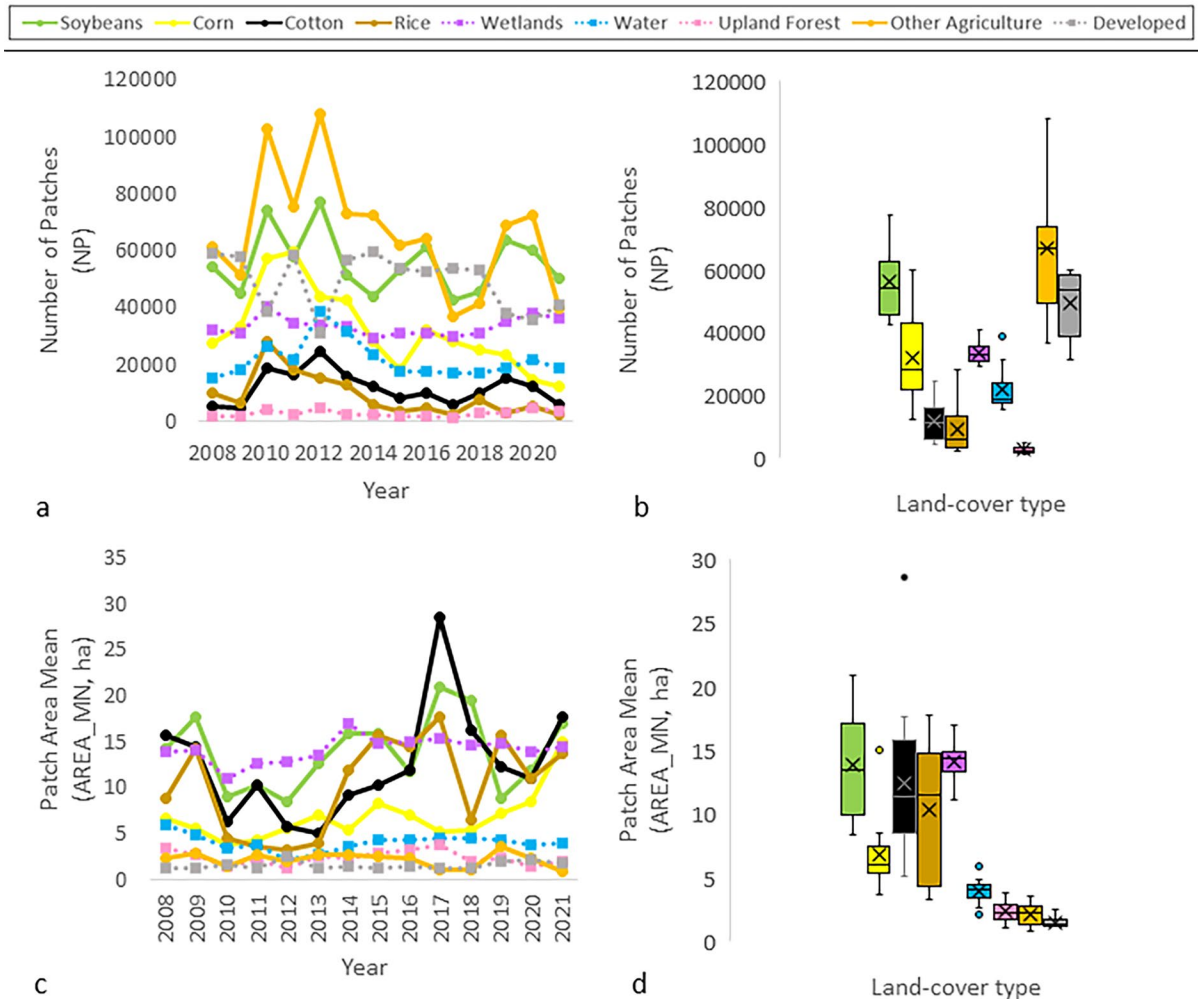
— Soybeans — Corn — Cotton — Rice — Wetlands — Water — Upland Forest — Other Agriculture — Developed



**Fig. 2** Composition metrics through time for each of the 9 classes: **a** Percentage of landscape (PLAND); **b** Box-and-whisker plot for PLAND; **c** Proportion of cultivated (solid

lines) and non-cultivated (hashed lines) lands in the Delta from 2008 to 2021; **d** Largest patch index (LPI); **e** Box-and-whisker plot for LPI

### CONFIGURATION METRICS I



**Fig. 3** Configuration metrics through time for each of the 9 classes [panel I]: **a** Number of patches (NP); **b** Box-and-whisker plot for NP; **c** Patch area mean (AREA\_MN); **d** Box-and-whisker plot for (AREA\_MN)

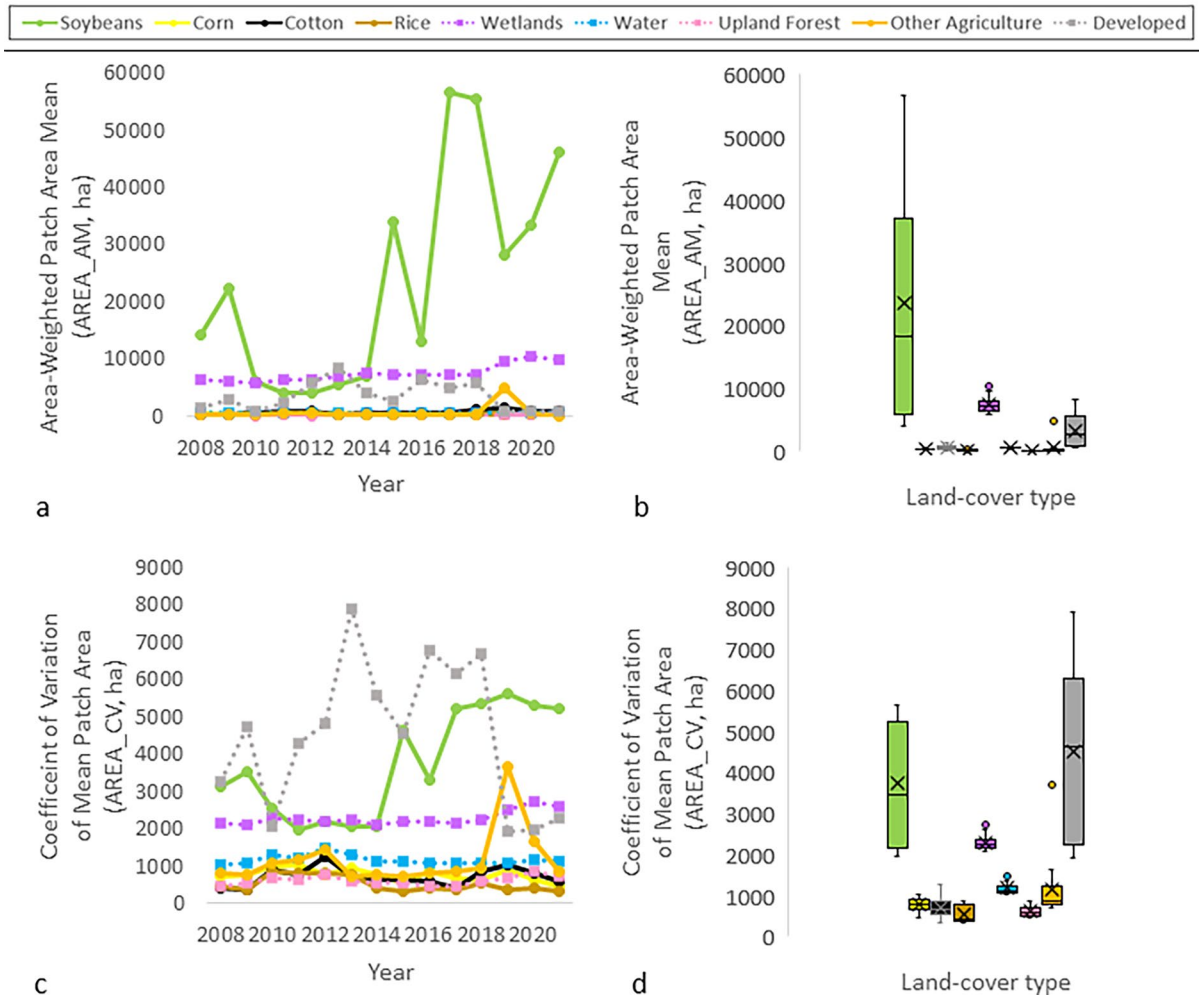
between complete dispersion and complete aggregation of land-cover types, indicating relative stability in spatial admixture (SI Table S10; Fig. 5e).

#### Landscape context

About a quarter of the Delta exhibited no spatial or temporal heterogeneity, representing stable monocultures (Franco et al. 2022). Such instances existed for each of the cultivated categories, especially soybeans. Soybean core areas were distributed throughout the Delta, with the highest concentration in the central and northern portions. Cotton had the second highest

area of stable monoculture, with core areas primarily in the northern Delta. “Other agriculture” had many small core areas, often near the Delta periphery. Rice and corn had very small core areas (Table 4; Fig. 6). When non-cultivated lands were considered, the largest core areas were associated with wetlands, distributed throughout the Delta. Areas of water were also highly stable, with core areas typically associated with rivers or lakes; an aquaculture core was observed within the south-central Delta (Leflore and Sunflower Counties [counties 9 and 13 in Fig. 1]). Developed core areas included urban centers and road networks, which were diffusely scattered throughout the region.

### CONFIGURATION METRICS II



**Fig. 4** Configuration metrics through time for each of the 9 classes [panel II]: **a** Area-weighted patch area mean (AREA\_AM); **b** Box-and-whisker plot AREA\_AM; **c** Coefficient of

variation of mean patch area (AREA\_CV); **d** Box-and-whisker plot for AREA\_CV

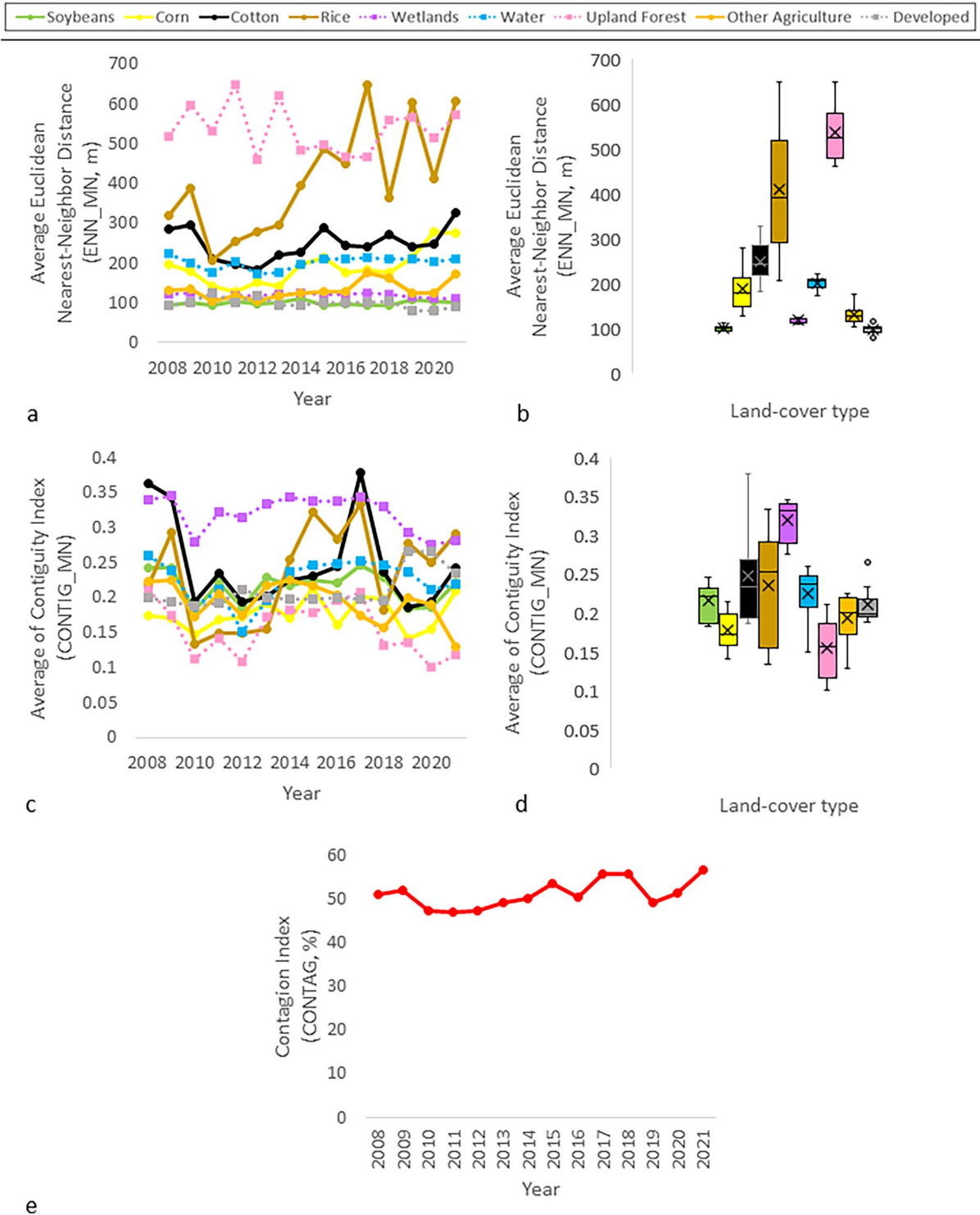
Lastly, upland forest core areas existed on the eastern periphery (Table 4; Fig. 6).

Landscape context as measured by per-pixel land-cover richness indicated that during our study period, most of the Delta was relatively stable in land cover (Table 5, Fig. 7). Transitions among three land-cover classes were the most common and occurred across ~33% of the landscape. Transitions among  $\geq 5$  classes were rare, at ~2% of the region in total (Fig. 7). Slightly over a quarter of the Delta never changed land-cover type (the 1-class richness category). Examining pixel trajectories for identification of instances of crop rotation, we found that sequential

field rotation was pervasive yet highly variable in space and time. Portions of the Delta that experienced continuous field rotation were especially rare, at ~1% of the region in total (Table 5).

Landscape context as measured by per-pixel land-cover change frequency indicated that most of the Delta experienced forms of land-cover change that included crop rotation as well as other forms of land-cover change, such as wetland inundation and urbanization (Table 6). Indeed, 73.25% of the Delta landscape experienced at least one land-cover class change, and on average, any given pixel experienced a change in land-cover type once every 5–6 years.

### CONNECTIVITY METRICS

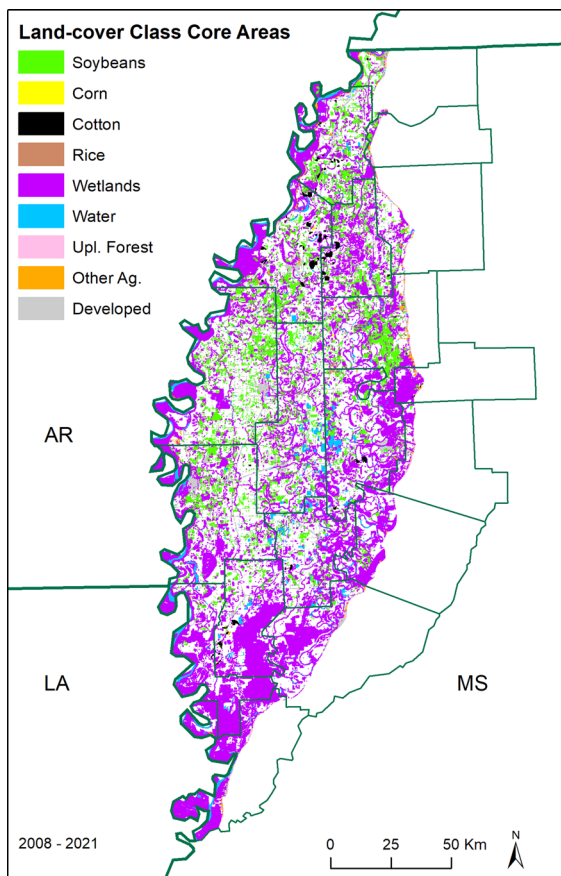


**Fig. 5** Connectivity metrics through time for each of the 9 classes: **a** Average Euclidean nearest-neighbor distance (ENN\_MN); **b** Box-and-whisker plot for ENN\_MN; **c** Average conti-

guity (CONTIG\_MN); **d** Box-and-whisker plot for CONTIG\_MN; **e** Landscape contagion of land-cover types (CONTAG)

**Table 4** Land-cover class core area distribution and proportional occurrences in the Yazoo-Mississippi Delta, 2008–2021

Land-cover class	# of pixels in class core areas (area in ha)	Land-cover class core area as % of total landscape
Soybeans	559,939 (50,340.51)	2.68
Corn	1498 (134.82)	0.01
Cotton	43,926 (3,953.34)	0.21
Rice	2509 (225.81)	0.01
Wetlands	4,090,338 (368,130.42)	19.49
Water	528,950 (47,605.50)	2.52
Upland Forest	32,742 (2,946.78)	0.16
“Other Agriculture”	12,289 (1,106.01)	0.06
Developed	338,349 (30,451.41)	1.61
Total	5,609,940 (504,894.16)	26.72



**Fig. 6** Spatial distribution of land-cover class core areas in the Delta

Relatedly, 22.63% of the Delta experienced land-cover change during more than half (7+ years) of the study period. Furthermore, 1% of the landscape experienced a class change every year; these areas occurred within every county of the Delta, although they tended to be concentrated in central and southern counties (Table 6, Fig. 8). These temporal patterns of land-cover change in the Delta reflected spatial patterns, with relative stability in peripheral portions of the region and areas with high turnover in the central Delta (Fig. 8). The areas with the least land-cover stability were often occupied by corn and cotton, whereas the most stable areas were wetlands (compare Figs. 1, 7, and 8).

Landscape context was also measured by per-pixel land-cover class majority (Fig. 9). Soybeans were the land-cover majority across 48.61% of the Delta, followed by wetlands as the land-cover majority across 25.57% of the Delta. Upland forest was the land-cover majority across only 0.30% of the Delta, ranking last (Table 7). Land-cover majority was indeterminate for small portions of the Delta (white gaps in Fig. 9).

Drivers of landscape pattern

During FB Era I, corn, rice, water, and “other agriculture” featured above-average occurrences. Soybeans, cotton, wetlands, upland forest, and developed each had below-average occurrences. During FB Era II, only soybeans featured above-average occurrences, with below-average occurrences for all other classes except for “developed,” which was exactly average. During FB Era III, soybeans again experienced above-average occurrence, as did cotton, wetlands, upland forest, and developed. Below-average occurrences for corn, rice, water, and “other agriculture” were observed. With respect to CRP, there was a peak in acreage in 2008 nation-wide and in Mississippi (Table 8), with decreases since then. Thus, some predicted influences of the Farm Bill were upheld in our data. For example, the prevalence of corn was above average during FB Era I (as predicted, given the 2008 Farm Bill’s promotion of ethanol). However, cotton did not exhibit a decline and then recovery (instead, it increased throughout). Finally, “other agriculture” (which included pasture/grassland) was at its lowest coverage during FB Era III, despite the 2018 Grassland Conservation Initiative (SI Table S2). As expected, CRP acreage declined over time (Table 8).

**Table 5** Land-cover richness distribution and proportional occurrences of field rotations in the Yazoo-Mississippi Delta, 2008–2021

# of land-cover classes present	# of pixels (area in ha)	% of landscape	# unique pixel trajectories	% unique pixel trajectories experiencing at least one sequential field rotation among soybeans, corn, cotton, rice, or “other agriculture” (area in ha)	% unique pixel trajectories experiencing at least seven sequential field rotations among soybeans, corn, cotton, rice, or “other agriculture” (area in ha)	% unique pixel trajectories experiencing continuous sequential field rotations among soybeans, corn, cotton, rice, or “other agriculture” (area in ha)
1*	5,617,995 (505,619.55)	26.75	9	N/A	N/A	N/A
2	5,424,304 (488,187.36)	25.83	64,721	44.74 (383,914.44)	20.00 (110,429.73)	0.02 (9,126.00)
3	6,863,963 (617,756.67)	32.68	616,901	84.30 (582,821.64)	32.49 (246,953.34)	<0.01 (7,849.71)
4	2,757,336 (248,160.24)	13.13	725,675	93.88 (241,638.21)	33.26 (120,813.12)	0.18 (1,399.14)
5	320,243 (28,821.87)	1.52	191,009	97.65 (28,380.42)	26.83 (10,514.07)	0.04 (21.69)
6	17,620 (1,585.80)	0.08	15,582	98.77 (1,568.52)	21.13 (365.67)	N/A
7	491 (44.19)	<0.01	484	99.59 (44.01)	18.39 (8.01)	N/A
8	4 (0.36)	<0.01	4	100.00 (0.36)	25.00 (0.09)	N/A
Total <sup>‡</sup>	21,001,956 (1,890,176.04)	100	1,614,385			

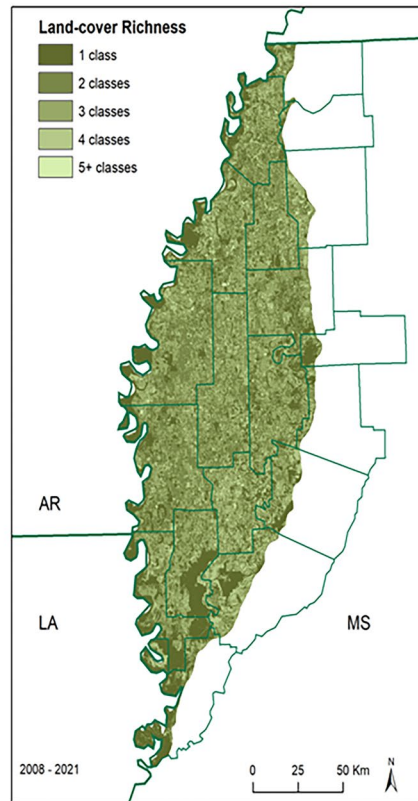
For a value of 1, a cell never changed land-cover type over our 13-year study period; the maximum number of changes observed was eight.

\*indicates the category from which land-cover class core area was derived (see Table 3)

<sup>‡</sup>Total pixel counts (and hectares) differ from those in Tables 6 and 7 because of processing of pixels along the Delta’s curved boundaries

**Fig. 7** Spatial distribution of context metrics: Land-cover Richness [panel I]

## CONTEXT METRICS I



Some landscape changes through time were coincident with changes in precipitation (Table 3). The most apparent trend observed was that for years of above-average growing-season rainfall, there were corresponding increases in the percent of the Delta composed of wetlands, most notably in 2014 and from 2019 to 2021. However, in the case above, which land-cover class experienced the corresponding decreases among those years differed (2014: corn and “other agriculture”; 2019: soybeans; 2020: corn, cotton, and “other agriculture”; 2021: cotton and “other agriculture”). For example, during relatively dry growing seasons, we observed general increases in the amount of corn (2010–2013) and soybeans (2015, 2017–2018). Landscape change was also coincident with changes in commodity prices (Table 3). Each primary crop experienced above-average prices in 2011, 2013, and 2021. Peak prices occurred in

2012 for both soybeans and corn, whereas peak price for cotton was in 2011 and the peak price for rice occurred in 2008. Each of the four primary crops experienced below-average prices between 2015 and 2017. The extent of cotton ( $R^2=0.21$ ,  $p=0.28$ ) and rice ( $R^2=0.06$ ,  $p=0.71$ ) were not well-predicted by price or precipitation or their interaction. For corn ( $R^2=0.61$ ,  $p=0.01$ ), price and precipitation in the previous year best predicted corn extent in the current year (i.e., lag effect evident), with no interaction term included in the best model. Specifically, higher price and lower precipitation in the previous year were associated with higher extent of corn in the current year. For soybeans ( $R^2=0.61$ ,  $p=0.02$ ), we found that extent was best predicted by price, precipitation, and their interaction in the same year (no lag effect evident). Lower precipitation in the same year was associated with higher extent of soybean cultivation,

**Table 6** Land-cover change frequency distribution in the Yazoo-Mississippi Delta, 2008–2021

Number of yearly changes	# of pixels (area in ha)	% of landscape
0	5,609,940 (504,894.60)	26.72
1	444,583 (40,012.47)	2.12
2	1,789,819 (161,083.71)	8.52
3	1,088,647 (97,978.23)	5.18
4	2,050,659 (184,559.31)	9.77
5	1,669,896 (150,290.64)	7.95
6	1,975,390 (177,785.10)	9.41
7	1,615,624 (145,406.16)	7.69
8	1,518,561 (136,670.49)	7.23
9	1,181,703 (106,353.27)	5.63
10	913,477 (82,212.93)	4.35
11	584,758 (52,628.22)	2.78
12	342,985 (30,868.65)	1.63
13	210,835 (18,975.15)	1.00
Total <sup>†</sup>	20,996,877 (1,889,718,.93)	100.00

A value of 0 indicates the number of cells that never varied in land-cover type; ~1% of the pixels (18,975.15 ha) on the landscape changed land-cover type each year over the 13-year timespan

<sup>†</sup>Total pixel counts (and hectares) differ from those in Tables 5 and 7 because of processing of pixels along the Delta's curved boundaries

and there was a positive interaction between soybean price and extent (the correlation between price and extent was more negative when precipitation is low, and more positive when precipitation was high). In summary, the amount of corn was positively associated with the previous year's prices and negatively with precipitation whereas soybean acreage was lower in high-precipitation years and more dependent on commodity prices. For detailed AIC values results, see SI Document 1.

## Discussion

Landscape change within the Delta during our study period was predominantly a function of agricultural activity and was broadly anticipated (Ambinakudige and Intsiful 2020; Yasarer et al. 2020). Wetlands were also key landscape features in the Delta, forming largely stable, contiguous patches. Other forms of land cover (water, developed, forest) were relatively rare. Our assessments illuminated contemporary

shifting mosaic patterns across the Delta. Moreover, our chosen metrics characterized stable monoculture, land-cover class core areas, spatial arrangements within and among land-cover classes, crop rotations, and other trajectory behaviors.

It should be noted that different landscape patterns may yield the same values for some metrics, and many metrics are sensitive to data resolution and spatial extent, complicating comparisons of different landscapes (Rommel and Csillag 2003). Despite these limitations, use of multiple metrics as diagnostic pattern indicators can shed light on how human activities affect disturbance regimes, biodiversity, and ecosystem services (see review by Rommel and Mitchell 2022). Some metrics may be valuable elsewhere but not in the Delta (and vice versa). For example, measures of connectivity may be especially useful in examining changes in flow regimes in wetlands (due e.g., to drought, damming, etc.), whereas an assessment of patch density may be warranted if metapopulation structure is suspected for a focal organism.

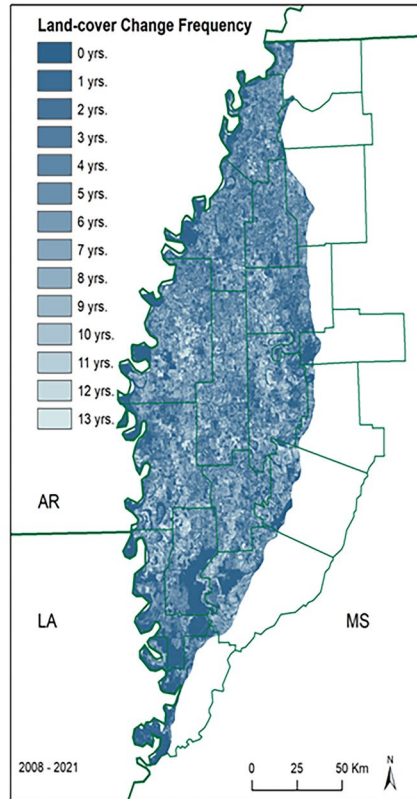
Of the 23 metrics we used, a smaller suite of 12 was able to adequately characterize landscape pattern and change in terms of composition (percentage of landscape covered by a given land-cover type), configuration (number of patches of a given land-cover type, average patch size, the coefficient of variation of average patch size, area-weighted average patch size, largest patch index), connectivity (average Euclidean nearest-neighbor distance, average contiguity, landscape contagion), and context (land-cover richness, land-cover change frequency, land-cover class majority). These metrics exhibited trends over time; the others did not, being either relatively static or varying greatly and erratically (SI Figs. S2–S12). Some metrics are redundant (e.g., average patch size and area-weighted average patch size, or contiguity and contagion), so an even smaller subset of 10 could be used for greater parsimony.

In land-cover composition (SI Table S2, Figs. 2a, b), soybeans were dominant in coverage and appeared to coalesce into larger patches (Figs. 2d, e). The increased prevalence of soybeans is locally regarded as a function of price and reduced costs of production. It has also been locally regarded as a function of international market effects, especially increased competition associated with cotton (personal communication, Dr. Martin Locke [NSL Director] and Lee Vi Haas [WQERU Biologist and producer]).



**Fig. 8** Spatial distribution of context metrics: Land-cover Change Frequency [panel II]

## CONTEXT METRICS II



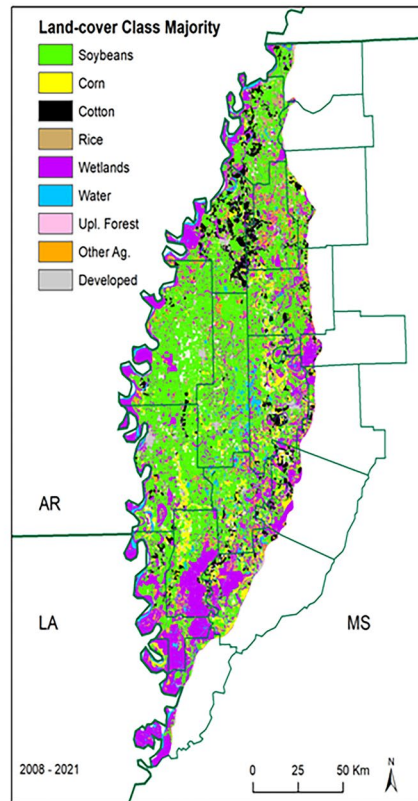
However, soybeans also experienced the greatest variation in coverage (Figs. 1b–o and 2a). The coalescence of soybeans into a larger monoculture has region-scale implications on fertilizer and water use, soil carbon, soil microbial diversity, yield, and other effects (Liu et al. 2006; Li et al. 2010). Such a trend towards landscape homogenization (potentially linked with federal agricultural policies such as the Farm Bill) occurs due to loss of land-cover diversity and structural heterogeneity, with knock-on negative effects on biodiversity through a reduction in resource availability. Incentivized conservation efforts (such as the Conservation Reserve Program in the US, or agri-environment schemes in Europe) are large-scale approaches to returning habitat value to cultivated landscapes (Batáry et al. 2015).

Among the other primary crops, corn was next-most variable in coverage, with areas of majority

coverage within Humphreys, Leflore, Sharkey, and Tallahatchie counties (counties 7, 9, 12, and 14 in Fig. 1). Cotton had the third-highest variation in coverage, with areas of majority coverage in Coahoma, Quitman, and Tunica counties (counties 3, 11, and 16 in Fig. 1). Rice area had been described as stagnant (Ambinakudige and Intsiful 2020), yet in later years of our study, we observed a decreasing trend in rice cultivation. Among the four major regional crops, rice had the lowest variation in coverage, with limited areas of majority coverage, and even fewer persistent land-cover class core areas. As noted previously, rice production is concentrated on poorly draining soils in the Delta and requires production practices that may be cost-intensive (e.g., standing water). Coupled, these factors likely explain in part the observed landscape patterns for rice. In early years of our study, a diffuse distribution of rice occurred in central and

**Fig. 9** Spatial distribution of context metrics: Land-cover Class Majority [panel III]

## CONTEXT METRICS III



**Table 7** Land-cover class majority distribution in the Yazoo-Mississippi Delta, 2008–2021

Land-cover class	Number of pixels (area in ha)	% of landscape
Soybeans	9,757,476 (878,172.84)	48.61
Corn	1,001,223 (90,110.07)	4.99
Cotton	1,180,580 (106,252.20)	5.88
Rice	198,190 (17,837.10)	0.99
Wetlands	5,133,321 (461,998.89)	25.57
Water	861,998 (77,579.82)	4.29
Upland Forest	60,431 (5,438.79)	0.30
Other Agriculture	1,078,161 (97,034.49)	5.37
Developed	801,268 (72,114.12)	3.99
Total <sup>‡</sup>	20,072,648 (1,806,538.32)	99.99

<sup>‡</sup>Total pixel counts (and hectares) differ from those in Tables 5 and 6 because of processing of pixels along the Delta’s curved boundaries

northern Delta counties. These historically rice-dominated areas were typically rotated with and then generally replaced by soybeans; this may reflect a shift in irrigation practices (Yasarer et al. 2020). Moreover, as rice production was not well-predicted by price or precipitation, it would suggest that other, more localized drivers (e.g., machinery access, labor availability) are likely important determinants for regional rice cultivation. For “other agriculture,” variation in coverage was the second highest among all nine land-cover types. “Other agriculture” had diffusely distributed majority occurrence areas, generally more common in eastern and southern portions of the Delta, and often near wetlands. Class core areas for “other agriculture” were often near the periphery of the Delta.

Among non-agricultural land-cover classes, wetlands accounted for the most surface area during all

**Table 8** CRP acreage in Mississippi

Year	CRP acreage
2008	894,913
2012	827,811
2014	759,117
2018	612,211
2021	550,790

years, with stability (persistence) in coverage, likely because they are too wet to farm and/or occur in areas that flood periodically. Large areas of wetlands were present along the Mississippi River and eastern limits of the Delta (often as components of or proximal to protected lands, e.g., Delta National Forest). Extensive flood control and aquifer management activities in the Delta likely account for some of the persistence we observed (Cobb 1992; Saikku 2005; Dakhllalla et al. 2016; Alhassan et al. 2019; Yasarer et al. 2020). Observed wetland stability was also likely influenced by wetland type, as large, bottomland-forested wetlands were more readily identifiable in the CDL. Persistent aquaculture was especially present in Leflore and Sunflower counties (counties 9 and 13 in Fig. 1).

As evidenced by variation in land-cover class changes, much of the Delta was dynamic. For any given pixel, the land cover richness ranged from one to eight classes, with most pixels fluctuating among three land-cover types (Table 5, Fig. 7). This three-class variation is consistent with regional crop rotation of soybeans, corn, and cotton (Ambinakudige and Intsiful 2020). The highest interannual variation in number of patches (Figs. 3a, b) was in the “other agriculture” class. This pattern may be due to (1) our methodological approach for double cropping among primary crops, albeit a relatively rare consideration (SI Table S1); (2) fluctuations with crops due to crop rotation, including to the fallow/idle cropland category; and/or (3) a consequence of flooding (fostering delayed planting/crop failure). Limited variation in the number of patches of upland forest, water, and wetland classes is consistent with the stability we observed in coverage for these land-cover types. The presence of numerous developed patches despite this land-cover type’s relative rarity on the landscape is indicative of the dispersed small settlements in the Delta. However, the high variability in the number and sizes of these developed patches may be inherent to the Cropland Data Layer, as “urban” (i.e., the

developed land-cover type) is known to be difficult to characterize (McIntyre 2011), and impervious surfaces are difficult to distinguish from some other land-cover types in remotely sensed imagery (Heintzman and McIntyre 2019).

Rice exhibited the greatest interannual fluctuations in mean patch size (SI Table S5, Figs. 3c, d). In later years of our study, the number of patches of rice generally declined and mean patch size generally increased. Similar later-year patterns were present for cotton as well. Notably, cotton had the overall highest mean patch size in 2017, when it also had the third-fewest number of patches. We attribute these patterns in part to crop rotation displacement of corn, resulting in a relatively denser distribution of cotton patches. Soybeans, although consistently among the top-4 land-cover classes with respect to mean patch area, also exhibited reciprocal oscillations between larger number of patches and lower mean patch area (e.g., in 2009 and 2017), which we attribute to rotation with cotton and corn or “other agriculture.” (These variations were particularly noticeable when controlling for the greater overall amount of soybeans on the landscape [Fig. 1b–o].) For corn, mean patch area was generally stable during early years, with greater oscillations beginning in 2013, and increasing to a class-specific peak in 2021; we attribute this peak to displacement of cotton and “other agriculture.”

Upland forest and rice had the greatest Euclidean nearest-neighbor distances and most variation in that metric (SI Table S8, Figs. 5a, b). The upland forest class was especially rare, with patches restricted to the extreme eastern fringe of the Delta. Although the distances among upland forest patches began high and remained so, the range of variation was far less than that for rice. The range of variation in distances among rice patches began to increase from 2010 onward, indicative of possible elimination within crop rotation regimes (being largely replaced by soybeans).

With respect to drivers of these patterns, changes within the Delta were influenced by precipitation and commodity price. During years with above-average growing season precipitation, we observed significant increases in wetlands and increases in “other agriculture,” likely representing flooded croplands being fallow/idle. During years with below-average growing season precipitation, we observed increases in soybeans and corn. Because the Delta is extensively irrigated via groundwater extraction (Dakhlalla et al. 2016; Yang et al. 2019; Yasarer et al. 2020; Lo and Pringle III 2021), some effects of precipitation on landscape composition may have been masked, especially if irrigation allowed producers to take advantage of higher commodity prices despite potentially dry conditions. Although we observed increases in soybeans during other dry times, our data suggest that the previous year’s conditions were not a strong predictor of soybean extent. Both cotton and rice were not well-predicted by price or precipitation. Comparatively, the influence of the Farm Bill as a driver of agricultural change was not as clear as the effect of commodity prices and precipitation on landscape cover. This is perhaps not surprising, given the long time spans associated with each Bill; changing prices and precipitation require more immediate responses. The landscape homogenization associated with agricultural intensification with respect to soybeans thus appears to be more a function of local to regional factors rather than federal-level policies.

These findings have potential relevance in resource management. For example, areas of spatial homogeneity and temporal stability may be relatively more vulnerable to pest outbreaks (Dalín et al. 2009). Additionally, the identification of the Delta as a shifting mosaic has implications on biodiversity conservation. For instance, Conservation Reserve Program lands would likely be the most fixed and stable portions of the landscape, at least on the decadal time scale of most CRP leases; if leases are not renewed, however, then it would be useful to know the locations of potential alternate habitats for displaced biodiversity, whether they are likely reachable, etc. Likewise, provision of ecosystem services such as pollination from native bees would vary in intensity over space and time, making it difficult to establish where supplemental pollination from domestic honey bees (*Apis mellifera*) would be needed. Finally, industries and individuals seeking to promote sustainable

and regenerative agriculture may influence landscape change for climate adaptation and to address food insecurity (Schattman et al. 2023). Our results suggest that such efforts would be most effective, at least on a regional scale, when allowing for short-term responses associated with commodity prices and weather. Our approach thus provides a useful model to management agencies for identifying areas of spatio-temporal heterogeneity or stability.

## Conclusions

Our study quantified changes in landscape patterns in the Delta. The metrics we calculated indicated relative stability in landscape composition over our study period, but with fluctuations in configuration, connectivity, and context that indicated latent landscape changes that metrics of composition did not detect.

Although the Farm Bill can provide billions of dollars in expenditures that influence the types and amounts of crops grown, this funding may be smaller and less responsive than changes in commodity prices. The overall effects of the different Farm Bills were mixed with respect to proportional coverage. Coupled with the general decline in CRP acreage, these results support the observation of a homogenizing agricultural environment in the Delta.

Abundances of soybeans and corn were significantly associated with precipitation and commodity prices, although their responses to temporal variation differed (lags for corn but not for soybeans). Patterns of cotton and rice were not explained by either precipitation or commodity prices. As our models were able to explain only ~60% of the variation in coverage of soybeans and corn (and did not perform well for cotton or rice), other drivers (e.g., irrigation, soil type or texture, crop insurance, development of transgenic crops, etc.) are likely important within the Delta (Yasarer et al. 2020).

Given the relative stability of most land-cover classes, similar ratios of cultivated vs. non-cultivated lands, and no net loss or gain of cultivated lands, the Delta appears to be a shifting mosaic whereby land-cover categories are not commonly eliminated but rather are repositioned. This also suggests that the Delta has likely plateaued in terms of cultivated land since the remaining lands (wetlands, forests, urbanized areas) are not optimal for agricultural production.

Thus, it is likely that future agricultural productivity can only be increased in the Delta through management strategies other than conversion of more land to cultivation.

In summary, our study addresses knowledge gaps in spatio-temporal heterogeneity of agroecosystems (Hopfenmüller et al. 2014; Corry 2019; Coffin et al. 2021) via an assessment of shifting mosaic dynamics within the Yazoo-Mississippi Delta. Our insights can guide agroecosystem optimization (Jeanneret et al. 2021; Tschardt et al. 2021) and be a model for examining similar agroecosystems (Yang et al. 2019; Jeanneret et al. 2021).

**Acknowledgements** This research was a contribution from the Long-Term Agroecosystem Research (LTAR) network. LTAR is supported by the United States Department of Agriculture (USDA). Mention of trade names or commercial products in this publication is solely for the purpose of providing specific information and does not imply recommendation or endorsement by the USDA. USDA is an equal opportunity provider, employer, and lender. We thank Lindsey Witthaus, Matt Moore, and Martin Locke of the National Sedimentation Laboratory for discussion. Comments from the Associate Editor, two anonymous reviewers, and from Justin Dawsey, Joe Girgente, Hannah Girgente, and Sean Sutor at Texas Tech University improved manuscript drafts. Additionally, USDA internal reviews from Jason Taylor of the National Sedimentation Laboratory and Alisa Coffin of the Southeast Watershed Research Unit augmented manuscript drafts

**Author contributions** All authors contributed to the study conception and design. Data processing and analysis were performed by LJH, E.J.L., and QDR. The first draft of the manuscript was written by LJH and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

**Funding** This study was supported by USDA-ARS Project # 6060–13660-009-00D and Project # 6060–13000-029-00D.

**Data availability** The datasets generated and used for this study are available through Ag Data Commons (<https://doi.org/https://doi.org/10.15482/USDA.ADC/1529589>).

## Declarations

**Competing interests** The authors have no relevant financial or non-financial interests to disclose.

**Open Access** This article is licensed under a Creative Commons Attribution 4.0 International License, which permits

use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

## References

- Alhassan M, Lawrence CB, Richardson S, Pindilli EJ (2019) The Mississippi Alluvial Plain aquifers: an engine for economic activity US Geological Survey Fact Sheet 2019–3003. US Geological Survey, Washington, D.C. <https://doi.org/10.3133/fs20193003>
- Ambinakudige S, Intsiful A (2020) Spatiotemporal analyses of changing cropping patterns and crop rotations in the Mississippi Delta. *J Miss Acad Sci* 65:228–236
- Batáry P, Dicks LV, Kleijn D, Sutherland WJ (2015) The role of agri-environment schemes in conservation and environmental management. *Conserv Biol* 29:1006–1016.
- Bennett AJ, Bending GD, Chandler D, Hilton S, Mills P (2012) Meeting the demand for crop production: the challenge of yield decline in crops grown in short rotations. *Biol Rev* 87:52–71.
- Boryan C, Yang Z, Mueller R, Craig M (2011) Monitoring US agriculture: the US Department of Agriculture, National Agricultural Statistics Service, Cropland Data Layer Program. *Geocarto Internat* 26:341–358.
- Cobb JC (1992) The most southern place on Earth: the Mississippi Delta and the roots of regional identity. Oxford University Press, New York, NY
- Coffin AW, Sclater V, Swain H, Ponce-Campos GE, Seymour L (2021) Ecosystem services in working lands of the southeastern USA. *Front in Sustain Food Syst* 5:541590.
- Corry RC (2018) Extending the string-of-lights metaphor to describe dynamism in agricultural landscapes. *Landscape Ecol* 33:1013–1022.
- Corry RC (2019) How measures of agricultural landscape patterns are affected by crop rotation dynamics. *Landscape Ecol* 34:2159–2167.
- CRS (Congressional Research Service) (2023) What is the Farm Bill? CRS Report RS22131. <https://crsreports.congress.gov/product/pdf/RS/RS22131>
- Cushman SA, McGarigal K, Neel MC (2008) Parsimony in landscape metrics: strength, universality, and consistency. *Ecol Indic* 8:691–703.
- Dakhlalla AO, Parajuli PB, Ouyang Y, Schmitz DW (2016) Evaluating the impact of crop rotations on groundwater storage and recharge in an agricultural watershed. *Agric Water Manage* 163:332–343.

- Dalin P, Kindvall O, Björkman C (2009) Reduced population control of an insect pest in managed willow monocultures. *PLoS one* 4:e5487.
- Fahrig L, Baundry J, Broton L, Burel FG, Crist TO, Fuller RJ, Sirami C, Siriwardena GM, Martin J-L (2011) Functional landscape heterogeneity and animal biodiversity in agricultural landscapes. *Ecol Lett* 14:101–112.
- Faulkner S, Barrow W Jr, Keeland B, Walls S, Telesco D (2011) Effects of conservation practices on wetland ecosystem services in the Mississippi Alluvial Valley. *Ecol Appl* 21(sp1):S31–S48.
- Franco S, Pancino B, Martella A, De Gregorio T (2022) Assessing the presence of a monoculture: from definition to quantification. *Agriculture* 12:1506.
- Frazier AE, Kedron P (2017) Landscape metrics: past progress and future directions. *Curr Landsc Ecol Rep* 2:63–72.
- Goslee SC (2020) Drivers of agricultural diversity in the contiguous United States. *Front Sustain Food Syst* 4:1–12.
- Gustafson EJ (1998) Quantifying landscape spatial pattern: what is the state of the art? *Ecosystems* 1:143–156.
- Gustafson EJ (2019) How has the state-of-the-art for quantification of landscape pattern advanced in the twenty-first century? *Landscape Ecol* 34:2065–2072.
- Han W, Yang Z, Di L, Mueller R (2012) CropScape: a Web service based application for exploring and disseminating US conterminous geospatial cropland data products for decision support. *Comput Electron Agric* 84:111–123.
- Heintzman LJ, McIntyre NE (2019) Quantifying the effects of projected urban growth on connectivity among wetlands in the Great Plains (USA). *Landsc Urban Plan* 186:1–12.
- Hohman WH, Halloum DJ (2000) A comprehensive review of Farm Bill contributions to wildlife conservation, 1985–2000. Technical Report, USDA/NRCS/WHMI-2000. US Department of Agriculture, Natural Resources Conservation Service, Wildlife Habitat Management Institute
- Hopfenmüller S, Steffan-Dewenter I, Holzschuh A (2014) Trait-specific responses of wild bee communities to landscape composition, configuration and local factors. *PLoS one* 9:e104439.
- Jaeger JA (2000) Landscape division, splitting index, and effective mesh size: new metrics of landscape fragmentation. *Landscape Ecol* 15:115–130.
- Jeanneret P, Aviron S, Alignier A, Lavigne C, Helfenstein J, Herzog F, Kay S, Petit S (2021) Agroecology landscapes. *Landscape Ecol* 36:2235–2257.
- Jelinski DE, Wu J (1996) The modifiable areal unit problem and implications for landscape ecology. *Landscape Ecol* 11:129–140.
- LaGro J (1991) Assessing patch shape in landscape mosaics. *Photogramm Eng Remote Sens* 57:285–293
- Landis DA (2017) Designing agricultural landscapes for biodiversity-based ecosystem services. *Basic Appl Ecol* 18:1–12.
- Li H, Reynolds JF (1993) A new contagion index to quantify spatial patterns of landscapes. *Landscape Ecol* 8:155–162.
- Li H, Reynolds JF (1994) A simulation experiment to quantify spatial heterogeneity in categorical maps. *Ecology* 75:2446–2455.
- Li C, Li X, Kong W, Wu Y, Wang J (2010) Effect of monoculture soybean on soil microbial community in the Northeast China. *Plant Soil* 330:423–433.
- Liu X, Herbert SJ, Hashemi AM, Zhang X, Ding G (2006) Effects of agricultural management on soil organic matter and carbon transformation—a review. *Plant Soil Environ* 52:531–543.
- Lo TH, Pringle HC III (2021) A quantitative review of irrigation development in the Yazoo-Mississippi Delta from 1991 to 2020. *Agronomy* 11:2548.
- McIntyre NE (2011) Urban ecology: definitions and goals. In: Douglas I, Goode D, Houck M, Wang R (eds) *The Routledge handbook of urban ecology*. Routledge Press, Milton park, pp 7–16
- Parajuli PB, Jayakody P, Sassenrath GF, Ouyang Y, Pote JW (2013) Assessing the impacts of crop-rotation and tillage on crop yields and sediment yield using a modeling approach. *Agric Water Manag* 119:32–42.
- Patton DR (1975) A diversity index for quantifying habitat “edge.” *Wildl Soc Bull* 3:171–173
- Pontius RG, Shusas E, McEachern M (2004) Detecting important categorical land changes while accounting for persistence. *Agric Ecosyst Environ* 101:251–268.
- R Core Team (2022) R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria, <https://www.r-project.org/>
- Rommel TK, Csillag F (2003) When are two landscape pattern indices significantly different? *J Geograph Syst* 4:331–351.
- Rommel TK, Mitchell SW (2022) Landscape pattern analysis. In: Francis RA, Millington JDA, Perry GLW, Minor ES (eds) *The Routledge handbook of landscape ecology*. Routledge Press, Milton Park, pp 283–311
- Riitters KH, O’Neill RV, Hunsaker CT, Wickham JD, Yankee DH, Timmins SP, Jones KB, Jackson BL (1995) A factor analysis of landscape pattern and structure metrics. *Landscape Ecol* 10:23–39.
- Riitters KH, O’Neill RV, Wickham JD, Jones KB (1996) A note on contagion indices for landscape analysis. *Landscape Ecol* 11:197–202.
- Risal A, Parajuli PB (2019) Quantification and simulation of nutrient sources at watershed scale in Mississippi. *Sci Total Environ* 670:633–643.
- Risal A, Parajuli PB, Dash P, Ouyang Y, Linhoss A (2020) Sensitivity of hydrology and water quality to variation in land use and land cover data. *Agric Water Manag* 241:106366.
- Saikku M (2005) *This Delta, This Land*. University of Georgia Press, Athens, GA
- Schatman RE, Rowland DL, Kelemen SC (2023) Sustainable and regenerative agriculture: Tools to address food insecurity and climate change. *J Soil Water Conserv* 78:33A–38A.
- Tscharntke T, Klein AM, Kruess A, Steffan-Dewenter I, Thies C (2005) Landscape perspectives on agricultural

- intensification and biodiversity-ecosystem service management. *Ecol Lett* 8:857–874.
- Tscharntke T, Grass I, Wanger TC, Westphal C, Batáry P (2021) Beyond organic farming—harnessing biodiversity-friendly landscapes. *Trends Ecol Evol* 36:919–930.
- Wickham JD, Ritters KH (1995) Sensitivity of landscape metrics to pixel size. *Int J Remote Sens* 16:3585–3595.
- Wu J, Jelinski DE, Luck M, Tueller PT (2000) Multiscale analysis of landscape heterogeneity: Scale variance and pattern metrics. *Geogr Info Sci* 6:6–19.
- Yang J, Ren W, Ouyang Y, Feng G, Tao B, Granger JJ, Poudel KP (2019) Projection of 21st century irrigation water requirement across the Lower Mississippi Alluvial Valley. *Agric Water Manage* 217:60–72.
- Yasarer LM, Taylor JM, Rigby JR, Locke MA (2020) Trends in land use, irrigation, and streamflow alteration in the Mississippi River Alluvial Plain. *Front Environ Sci* 5:8–66.
- Zeileis A (2019) *dynlm*: Dynamic Linear Regression. R package version 0.3–6, <https://cran.r-project.org/package=dynlm>

**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.