An Assessment of an Agri-environmental Policy on Landscape Connectivity for Wildlife

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Abstract

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Agricultural land conversion has resulted in the loss of 95-98% of tallgrass prairie habitat in the US. The rapid expansion and intensification of agricultural practices has played a pivotal role in meeting the ever-growing global demand for food. However, this intensification has come at an undeniable cost to the environment, especially in the form of habitat loss. In a high intensity agricultural system such as the US corn belt, agri-environmental policies can have a significant impact on remnant ecosystems. One common policy in this regard is the implementation of riparian buffer strips, designed to reduce pollution and soil runoff from agricultural fields into adjacent waterways. However, these strips also have the potential to provide critical habitat for wildlife, fostering landscape connectivity and aiding in the conservation of biodiversity. While the federal government provides incentives to encourage the creation and maintenance of buffer strips, the only state in the corn belt to require them is Minnesota. I built a machine learning model to classify high-resolution aerial imagery of this region over a time series from 2008, before policy implementation, to 2021, after implementation. The model separated agricultural

and developed lands from permanent vegetation with the assumption that permanent vegetation will support the dispersal of wildlife more effectively than corn and soy monocrops. These classified maps were quantified using landscape connectivity metrics and compared between MN and other corn belt states, which collectively served as a synthetic control. The synthetic control model estimated high, positive impacts of buffer strip policy on landscape connectivity metrics.

Contents

INTRODUCTION

Agricultural land conversion has resulted in the loss of 95-98% of tallgrass prairie habitat in the US since the advent of industrial agriculture (Samson et al., 2004). The rapid expansion and intensification of agricultural practices has played a pivotal role in meeting the ever-growing global demand for food and other goods. However, this intensification has come at an undeniable cost to the environment. The growth of agriculture is one of the largest drivers of habitat loss and fragmentation for wildlife, far exceeding the impacts of other types of human land conversion and disturbance(Samson et al., 2004; Tscharntke et al., 2005). It is also one of the largest contributors to soil erosion and the degradation of water quality (Schilling et al., 2023; Vought et al., 1995). Intensifying agricultural landscapes increasingly threaten biodiversity, disrupting the balance between human resource needs and the health of natural ecosystems.

In recognition of these problems, implementing agri-environmental policies has become a common method of mitigation. Riparian buffer strips and conservation buffers are frequently implemented practices, often through governmental policies such as subsidies. These strips, consisting of permanent vegetation along water bodies, are designed to reduce pollution and soil runoff from agricultural fields into adjacent waterways. However, if designed and implemented correctly, the positive impacts of buffer strips could extend beyond these intended benefits. In addition to mitigating the detrimental effects of agriculture, these strips have the potential to provide crucial habitat for wildlife, fostering landscape connectivity and aiding in the conservation of biodiversity (Cole et al., 2015; Fletcher et al., 2023; Krauss et al., 2010; Öckinger &

Smith, 2007). Minnesota has taken a proactive step by enacting legislation mandating the implementation of buffer strips along water bodies, the only state in the Corn Belt to do so. Despite their potential for wildlife conservation, no research on their effect on wildlife has been conducted since this law's enactment. Additionally, no study has examined any policy-specific impacts on connectivity relating to buffer strips.

This study aims to analyze the impact of Minnesota's buffer strip law on mitigating the adverse effects of agriculture, employing advanced remote sensing and modeling techniques to evaluate land-use change and its implications for wildlife dispersal. By combining these methodologies, I can assess changes in buffer strip areas across Corn Belt states. While typically unable to substitute for pristine prairie environments, extensive buffer strips may help provide additional resources, reduce some breeding mortalities, and connect higher-quality protected areas for multiple wildlife species (Evans et al., 2014; Lukens et al., 2020; Öckinger & Smith, 2007; U. S. Fish and Wildlife Service, 2016).

BACKGROUND

Landscape Fragmentation

Landscape fragmentation refers to breaking up large, continuous habitats into smaller, isolated fragments, a common effect of human development. One of the most significant drivers of fragmentation is the conversion of habitat into agricultural lands, which comprise about 40% of Earth's land area and more than half of the US (Bigelow & Borchers, 2017). Landscape fragmentation and habitat loss can significantly impact a region's biodiversity and ecosystem services. The loss of large, interconnected habitats can reduce the number of species present, increase the risk of local extinctions, and alter the overall structure of ecosystems (Haddad et al., 2015; Krauss et al., 2010; Nelson et al., 2009). Fragmented landscapes can also create edge habitats, which have different environmental and microclimate conditions than the habitat's interior. This can lead to changes in the distribution and behavior of species, as well as increased vulnerability to invasive species and disturbances (Haddad et al., 2015; Marvier et al., 2004). Fragmentation can also severely limit wildlife dispersal, reducing the interaction and colonization of adjacent patches (Haddad et al., 2015; Hanski, 1998; Prugh et al., 2008).

In addition to its impacts on biodiversity, landscape fragmentation can also significantly affect the ecosystem services provided by an area (Balvanera et al., 2001; Tscharntke et al., 2005). Non-market ecosystem services refer to the benefits humans derive from healthy ecosystems, such as air and water filtering, pollination, and climate regulation, differing from monetized, market ecosystem services such as food and fiber production. Fragmented landscapes can disrupt these non-market ecosystem services in several ways. For example, the loss of large, continuous habitats to provide market services can reduce the ability of ecosystems to filter and purify water, leading to decreased water quality (Schilling et al., 2023; Smith et al., 2013). Similarly, the loss of pollinators such as bees and butterflies, due to fragmentation, can negatively impact food production (Balvanera et al., 2001; Ricketts et al., 2006). This can also make ecosystems and agricultural systems more vulnerable to invasive species, creating high costs for farmers and taxpayers in the form of herbicide use and other management (Pimentel et al., 2005).

When restoring landscape connectivity, bottlenecks for dispersal are found much more frequently across more human-modified landscapes, especially those with high agricultural land use (Haddad et al., 2015; Wimberly et al., 2018). Only relatively scarce and narrow sections of natural remnant vegetation exist within agricultural landscapes. Additionally, in Corn Belt states (Illinois, Iowa, Indiana, Kansas, Michigan, Minnesota, Wisconsin, Missouri, Ohio, North Dakota, and South Dakota), the matrix between these patches is predominantly corn and soybeans and is found to be particularly low value for wildlife(Brandmeier et al., 2023; Tscharntke et al., 2005; Wimberly et al., 2018). Since agriculture is estimated to make up the majority of land in the US (Bigelow & Borchers, 2017), any significant improvement in wildlife resources or permeability within agricultural lands could translate into considerable benefits for habitat connectivity and population resilience for multiple species. This is especially true for smaller and edge-adapted species, such as many arthropods, birds, reptiles, and amphibians (Best et al., 1997; Cole et al., 2015; Cunningham et al., 2008; Marczak et al., 2010; McCracken et al., 2012), as well as native plants (Brudvig et al., 2009; Damschen et al., 2019; Stutter et al., 2012).

Agricultural Policy

Agricultural conservation laws in US states and localities exist across a broad spectrum. Many of these laws mirror federal laws, which are typically voluntary conservation, providing direct monetary incentives, tax incentives, or free assistance. One recent different approach is in the state of Minnesota at the northern edge of the US Corn Belt. In 2015, Minnesota enacted a "buffer law" that required the installation of permanently vegetated buffers on most waterways – about 15m on all sides of lakes, rivers, and streams and about 5m on each side of ditches (Fig. 1). Since the passage of the law, the state estimates 98% compliance. This extra 30m and 10m of permanent vegetation is mainly intended to provide ecosystem services by filtering phosphorus, nitrogen, and sediment. No other state in the Corn Belt has a similar law that forces the implementation of buffer strips. This presents an excellent model for studying the landscape effects of this type of "command-and-control" (CAC) conservation measure compared to the more common voluntary measures. CAC laws establish criminal or civil penalties for violations. This is opposed to incentives, which offer money or other aid when actions are taken, or taxes, effectively charging a fee to be able to take actions.

Most agriculture in the US occurs on private lands, which can be challenging to manage, but are essential for the conservation of imperiled species. Over the last 30 years, endangered species have lost 2.25 times the amount of habitat on private lands compared to public lands in the US (Eichenwald et al., 2020). A variety of federal policies have been instituted in an attempt to promote conservation in these (and other) regions, such as the Agricultural Conservation Easement Program (ACEP), Conservation Reserve Program (CRP), Conservation Reserve Enhancement Program (CREP) the Environmental Quality Incentives Program (EQIP), the Clean Water Act (CWA), the Conservation Stewardship Program (CSP), and Working Lands for Wildlife (WLW). Most of these programs offer assistance in conservation planning and financial compensation if the conservation actions meet their standards, effectively subsidizing farmers to take conservation action. This is similar to how they may be subsidized for the crops they choose to grow. The notable exception is the CWA, a CAC law containing criminal enforcement penalties.

Figure 1. Clockwise from upper left: NAIP imagery of a riverine buffer strip in MN, a photo from the ground of this buffer strip, and a photo from the ground of a nearby ditch buffer strip.

In Minnesota, there was widespread opposition to the new buffer strip law, as it has required farmers to take portions of their land out of production. The value lost from this lessened production has not been evaluated, nor has the total area converted. However, using the state's buffer map, I calculated the total area affected to be 2,085 km^2, about

1% of the state's 206,232 km^2 land area. Using current agricultural land value by county, this translates to about $1.5 billion of private land affected by the law, although certainly not all of this land would hold the full value of agricultural land. Nevertheless, this has led to opposition of the bill, especially considering how public waters are distinguished from ditches in the policy, which can be buffered at much smaller widths. The dataset from which these current determinations were made was created with a 1980s land survey based mainly on drainage size. The statutory definition of public waters in MN includes water bodies with a drainage area greater than two square miles. This results in any waterway with a drainage area of greater than two miles needing to be buffered at 15m on both sides, whereas those with smaller drainage areas only need 5m. This land survey is due to be updated in 2025.

Just as the most common intention behind riparian buffers is to enhance water quality, the bulk of the scientific literature behind buffer strips focuses on their potential use in the filtration of fertilizer and sediment (Schilling et al., 2023; Sirabahenda et al., 2020; Smith et al., 2013; Vought et al., 1995). The results of these studies have been somewhat mixed, with most modeled results showing strong positive impacts on water quality, but empirical studies showing very significant differences in their effectiveness based on local conditions.

While some research has been conducted on how conservation buffers can promote landscape connectivity, this research has mainly been on small scales with little consideration for landscape effects. For many species, particularly plants, insects, and birds, small amounts of additional areas that consist of permanent vegetation significantly impact their populations and metapopulations (Brudvig et al., 2009; Cole et al., 2015; Dover et al., 2000; Fletcher et al., 2023; Jauker et al., 2009; Lind et al., 2019; Meinzen et al., 2024; Öckinger & Smith, 2007; Pavlacky Jr. et al., 2022; Reeder et al., 2005; Schwartz & van Mantgem, 1997). This is especially true when the surrounding matrix is as resource-limiting as it is in the Corn Belt.

Buffer Strip Quality

While landowners in Minnesota are required to install buffer strips on the specified riparian areas, they may be able to receive partial funding to do so. The type of funding they receive determines the required plantings in the buffer. If they install the buffer strips without government aid (monetary or planning), the only requirements are that the buffer strip consists of permanently rooted vegetation and excludes invasive species. Programs such as CRP and EQIP may require native vegetation depending on the funding goals, whereas CREP funding and Reinvest in Minnesota funding require the sole use of native plants. Funding from the Minnesota Board of Water and Soil Resources strongly encourages the use of native species, but specifics are left up to the discretion of local conservation districts. These programs likely have a major impact on the quality of any habitat provided, so an in-depth review of how much the newly installed buffer strips utilized government programs would be valuable.

Remote Sensing

When monitoring land-cover change in the past 50 years, the imagery of choice has typically been the Landsat series of satellite imagery. Starting with 80m spatial resolution and progressing to the modern standard of 30m in 1982, Landsat imagery has served as an excellent tool to monitor landscape change across large areas with high temporal resolution. More recently, Sentinel imagery has allowed for similar land cover analysis at a 10m resolution. In the US, widely available National Agricultural Inventory Program (NAIP) imagery (at a 1m or less spatial resolution) is rarely used for land-cover analyses due to its many drawbacks. The main drawbacks of doing so are large data sizes, making image processing difficult, low temporal resolution (~3 years), low spectral resolution (3 or 4 bands), inconsistencies due to different contractors hired to collect imagery, and historical imagery going back to only 2002. Despite these drawbacks, the high spatial resolution makes NAIP the only way to evaluate fine land-cover changes on a landscape scale across the US. Some researchers have found success (Maxwell et al., 2019; Prasai et al., 2021), but they have been limited to smaller regions and some have only used pixel-based methods.

Machine Learning

The use of machine learning has become an essential aspect of analyzing and interpreting large amounts of imagery data. As the quantity and resolution of imagery have gotten higher, other methods of image analysis have become less efficient and more challenging due to the amount of data and complexity of patterns (Blaschke, 2010; Breiman, 2001; Sheykhmousa et al., 2020).

One of the key applications of machine learning in remote sensing is land-cover classification. By training models to recognize patterns in spectral data, we can classify different types of land cover based on their unique spectral signatures. Random forest machine learning models are especially suited to this because they can handle large datasets with high dimensionality and are effective at modeling complex, non-linear relationships between the input features and the target classes (Breiman, 2001; Sheykhmousa et al., 2020). This works by constructing an ensemble of decision trees during training and outputting the mode of the classes. This approach reduces the risk of overfitting that can occur with single decision trees and improves the overall accuracy of the classification.

Structural Connectivity

Attempts at quantifying landscape connectivity began shortly after the concept was defined (Henein & Merriam, 1990; Merriam, 1984). It was especially popularized by the software FRAGSTATS (McGarigal & Marks, 1995). Subsequently, many attempts have been made to estimate how well structural connectivity can predict functional connectivity for populations or species, with mixed results. However, depending on the specific metrics used, some circumstances allow for higher-value predictions, such as if attempting to make predictions for generalist and edge-adapted species, with structural connectivity having a high correlation with dispersal potential and survival (Calabrese & Fagan, 2004; Fagan & Calabrese, 2006; Henein & Merriam, 1990; Jauker et al., 2009; Schumaker, 1996). Importantly, these are the species that can more easily be managed in high-intensity agricultural environments, making landscape structure a valuable predictor of their ability to occupy and disperse through these regions.

Synthetic Controls

Synthetic controls, as popularized by Abadie et al. (2010) and Abadie & Gardeazabal (2003), can be necessary with non-experimental studies to isolate the treatment variable from the time variable. Synthetic controls are often used in sociological studies (and becoming more common in conservation) when studying broadscale events that have already occurred. This readily lends itself to the broad scale of ecological landscapes, where the traditional treatment and control groups of an experimental setup are infeasible.

Research Objectives

The objective of this study was to build a successful machine-learning model that could classify NAIP data from anywhere in the US Corn Belt into areas of permanent vegetation and the opposed. Then, these classified maps could be used to calculate structural connectivity metrics and establish a causal relationship between the MN buffer law and increasing habitat connectivity. This causality could be inferred through a synthetic control of other Corn Belt states. A synthetic control creates a model of a counterfactual MN without the existence of the law to be compared to the factual MN. This attempts to provide evidence that CAC buffer laws may have additional co-benefits related to conservation.

METHODS

Machine Learning Classification

I first built a machine-learning model to classify approximately 10 terabytes of 4-band NAIP imagery obtained from the Google Earth Engine database to accomplish these objectives. The model also included a much smaller amount of Landsat 8 data, which was used to assist in differentiating between cropland and permanent vegetation, which can look similar in leaf-on imagery such as NAIP. The study area consists of all US HUC 10 (watersheds) with 50% or greater soybean and corn land cover, as measured from the USDA Cropland Data Layer from the first study year of interest, 2008. This includes portions of North Dakota, South Dakota, Nebraska, Iowa, Missouri, Wisconsin, Michigan, Indiana, Ohio, and Illinois (Fig. 2). The time period included all possible images between 2008 and 2023. 2008 was selected for model initiation as it was the first year the NAIP infrared band was collected in this region.

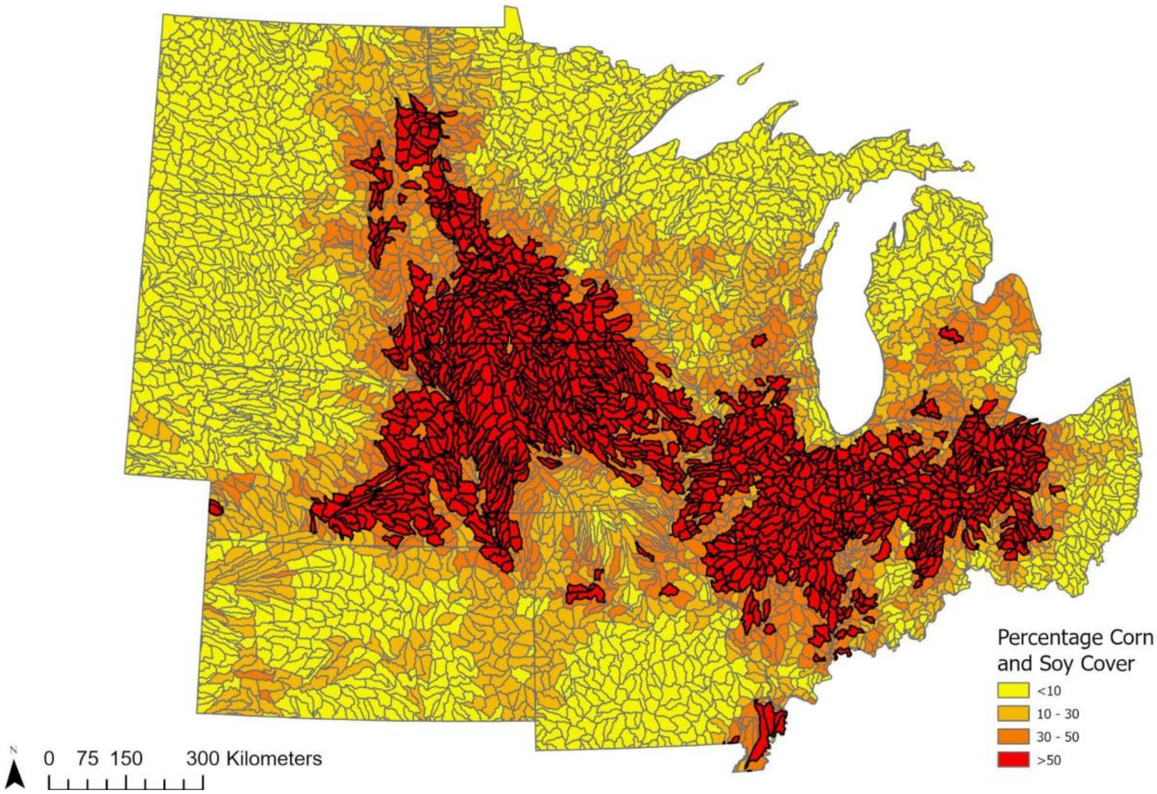


Figure 2. Map of the Corn Belt with HUC 10 watersheds shaded by the percentage of corn and soy land cover. The selected watershed for the study area (>50% corn and soy) is shaded in red and highlighted in black

Due to the processing power necessary to segment and classify this amount of data, I used the cloud processing services of Google Cloud/Google Earth Engine (GEE) to run the scripts necessary for data analysis. GEE is a cloud processing system that operates on Google Cloud servers. It can mainly be accessed using either a JavaScript or a Python interface. The Python interface was used in this study because it has a diverse library, extensive documentation, and greater flexibility, making it easier to apply to this research.

The first step of image classification was to segment the images into objects to avoid pixelation in the final maps. This was done using the SNIC (Simple Non-Iterative Clustering) tool package in the GEE Python interface (Achanta & Susstrunk, 2017; Gorelick et al., 2017). The non-iterative design of SNIC makes it computationally efficient which is essential for handling large datasets (Achanta & Susstrunk, 2017). It preserves feature boundaries by clustering pixels into superpixels that closely follow natural edges, which is crucial for accurately delineating narrow features such as the target buffer strips. SNIC allows for object-based image analysis (as opposed to pixel-based), reducing the "salt-and-pepper" effect and improving classification accuracy.

The image to be classified consisted of 1m resolution, 4-band (RGBN) NAIP imagery merged with a resampled Landsat 8 composite band. This band consisted of a median image for each study year at a 30m resolution converted and resampled into a single band NDVI at a 1m resolution. This allowed for an extra differentiator (with low weight to account for downscaling errors) between crops that are only present part of the year and permanent vegetation that wildlife will use more effectively. This may lead to false negatives (in identifying permanent vegetation) but should significantly reduce any false positives.

Once segmented, each segment was assigned its SAVI (soil-adjusted vegetation index), NDWI (normalized difference water index), area, perimeter, length, width, original red/green/blue/infrared bands, and their standard deviations. These characteristics were selected as they were likely to have the greatest differences between areas of permanent vegetation and nonpermanent vegetation. This method presumed that buffer strips would have a distinct shape, size, and spectral signature.

Following segmentation, the machine learning model was trained on these images using a random forest classification (Breiman, 2001). Random forest was chosen especially for its robustness to noise and ability to handle unbalanced datasets, which is especially relevant to NAIP data in the study area. This model was trained by using National Land Cover Database (NLCD) data from each study year to generate training points for each potential class, consisting of equivalent classes to NLCD. A total of 15,000 points were sampled across all classes, proportional to the expected class distribution. A false positive rate for permanent vegetation classes less than 10% was established to be considered successful (Fig. 3) (Maxwell et al., 2019).

A random forest classifier with 100 trees was trained on the extracted features, with the training data split into 70% for training and 30% for validation. The classifier was applied to each watershed to produce land-cover classifications. Classification accuracy was assessed using confusion matrices, with both training and test accuracies calculated for each classified watershed. The process was repeated multiple times to account for variability in the results. Confusion matrices were also generated for the accurate classification of permanent vegetation (as opposed to the aforementioned confusion matrices of all 16 potential classes).

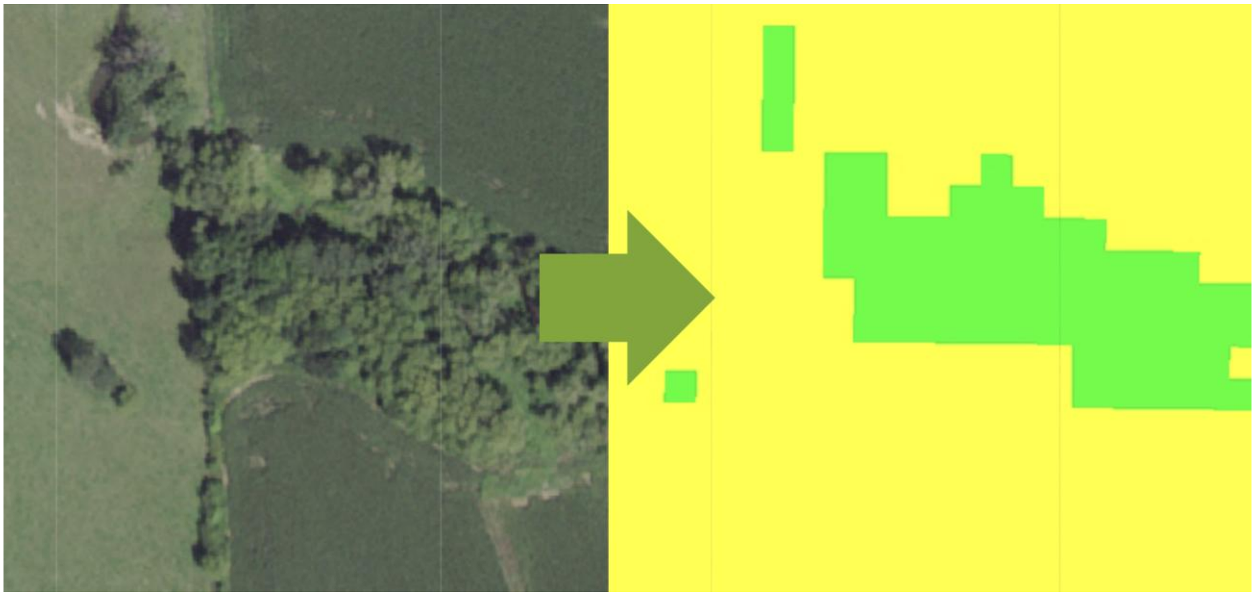


Figure 3. An example of NAIP imagery then classified into agricultural matrix and potential habitat

Landscape Metrics and Regression

Once classified, the data for MN was split from the other states so that the remainder could serve as a synthetic control. After each dataset was exported, the images were analyzed using the landscapemetrics package in R (Hesselbarth et al., 2019; R Core Team, 2021) to obtain a series of connectivity metrics deemed appropriate for this landscape. The metrics included cohesion, number of patches, effective mesh size, and percent of landscape. Cohesion was chosen because it measures the physical connectedness of habitat patches within the landscape (Hesselbarth et al., 2019; Schumaker, 1996). It quantifies how aggregated or clumped habitat patches are by considering both the size of patches and their proximity to each other. A higher cohesion value indicates that habitat patches are more connected, which can facilitate the movement and dispersal of organisms across the landscape. This impacts organisms that might disperse through a landscape; the closer patches are together, the more likely dispersal can occur through the matrix. This metric has been rated as having the highest correlation with functional connectivity for dispersing wildlife (Bishop-Taylor et al., 2018; Hesselbarth et al., 2019; Schumaker, 1996). Effective mesh size was chosen as an alternative measure of aggregation that can achieve different results from cohesion, having only a small positive correlation (Hesselbarth et al., 2019). Mesh quantifies the probability that two randomly chosen points within the landscape are connected without being separated by barriers (Jaeger, 2000). It reflects the degree of fragmentation by considering both the size and distribution of habitat patches. A larger effective mesh size indicates a less fragmented landscape with larger, more contiguous habitat areas. Differently, number of patches is not a measure of connectivity, as an increase in the number of patches often indicates fragmentation is occurring. However, an increase in number of patches could also indicate that new habitat is being created. Percentage of the landscape is also not a literal measure of connectivity, but is still an important indicator of available habitat.

Each metric was evaluated separately using the R package CausalImpact (Brodersen et al., 2015). This technique creates a synthetic control (a counterfactual MN as if the buffer law had not been enacted) to compare to the factual MN. By using a synthetic control, I attempted to isolate the effect of the buffer law in 2015 from the effects of time or how the landscape of Minnesota may have been changing already (such as from agricultural development, climate change, social attitudes, economic changes, etc.). If there were an impact of the buffer law, a change to the rates of change of the landscape metrics would be expected that was different than any changes in those of the synthetic control at the time of its implementation.

Using these equations, the CausalImpact package constructed a synthetic control for Minnesota and estimated the causal effect of the buffer law on each landscape connectivity metric. The model compared the observed post-intervention data from Minnesota to the synthetic control, allowing us to quantify the impact of the buffer law while accounting for temporal trends and the influence of other states. The CausalImpact package uses a Bayesian structural time-series model, defined by two main equations, the observation equation and the state equation.

Finally, an additional null test was conducted for percentage of landscape within buffer strips and percentage of landscape outside of buffer strips. Only percentage of landscape was used, as other metrics are only applicable to whole landscapes.

Observation Equation

$$y_t = Z_t^T \alpha_t + \epsilon_t$$

Where:

y_t is the observed landscape metric (cohesion, effective mesh size, number of patches, or percent of landscape) at time t

Z_t is a vector of covariates at time t, representing the landscape metrics from other Corn Belt states

α_t is a vector of latent state variables

ϵ_t is a Gaussian error term, $\epsilon_t \sim N(0, \sigma_\epsilon^2)$

This equation describes what is actually seen in the data, stating that our observed landscape metric is dependent on Z_t, or the hidden effects that we are trying to extract from our control as well as some random noise.

State Equation

$\alpha_{t+1} = T_t\alpha_t + R_t\eta_t$

Where:

T_t is the state transition matrix

R_t is the control matrix

η_t is a Gaussian error term, $\eta_t \sim N(0, Q_t)$

This equation describes how the hidden effects change over time, stating that α_{t+1}, or the hidden effects at the next time step, are dependent on the current hidden effects and some random changes.

Local Level Component

$\mu_{t+1} = \mu_t + \delta_t$

$\delta_{t+1} = \delta_t + \zeta_t$

Where:

μ_t is the value of the trend at time t

δ_t is the local trend at time t (slope)

ζ_t is a Gaussian error term, $\zeta_t \sim N\left(0, \sigma_\zeta^2\right)$

Then, the model includes a static regression that accounts for the hidden effects found in other Corn Belt states:

Static Regression

βx_t

Where:

β is a vector of regression coefficients

x_t is a vector of covariates at time t, representing the landscape metrics from other Corn Belt states

Additional predictive variables were used by year, including Palmer Drought Severity, May precipitation, acres enrolled in CRP, and crop cash receipts.

Resistance Modeling

A resistance model was built for a random MN watershed using Circuitscape, a utility for modeling landscape connectivity based on circuit theory (Dickson et al., 2019; Shah & McRae, 2008). This software takes a patch or habitat map along with a resistance or conductance map and measures the electrical resistance or conductance of a landscape. The habitat map serves as electrical sources and allows for the measurement of the ability of the circuit to function between each pair of sources. This was performed as one additional example of landscape connectivity, as it is measured in a more functional way than a purely structural metric like patch cohesion (Dickson et al., 2019). This resistance model used the PADUS (protected areas database of the US) areas in the watershed as the electrical sources and the binary classified maps of this watershed for each available year to act as the resistance maps.

RESULTS

Machine Learning Classification

The machine learning classification was successfully executed using a random forest classifier. The model classified the imagery into 16 land-cover classes (15 when excluding the snow class), achieving an overall accuracy exceeding 65%. While this overall accuracy may appear modest, it is important to note that misclassifications predominantly occurred between spectrally similar and closely related classes. This is illustrated in the misclassification network graph (Fig. 4), where most errors are between closely related classes such as between varying intensities of urbanization, between wetlands, or between grasslands, pasture, and crops.

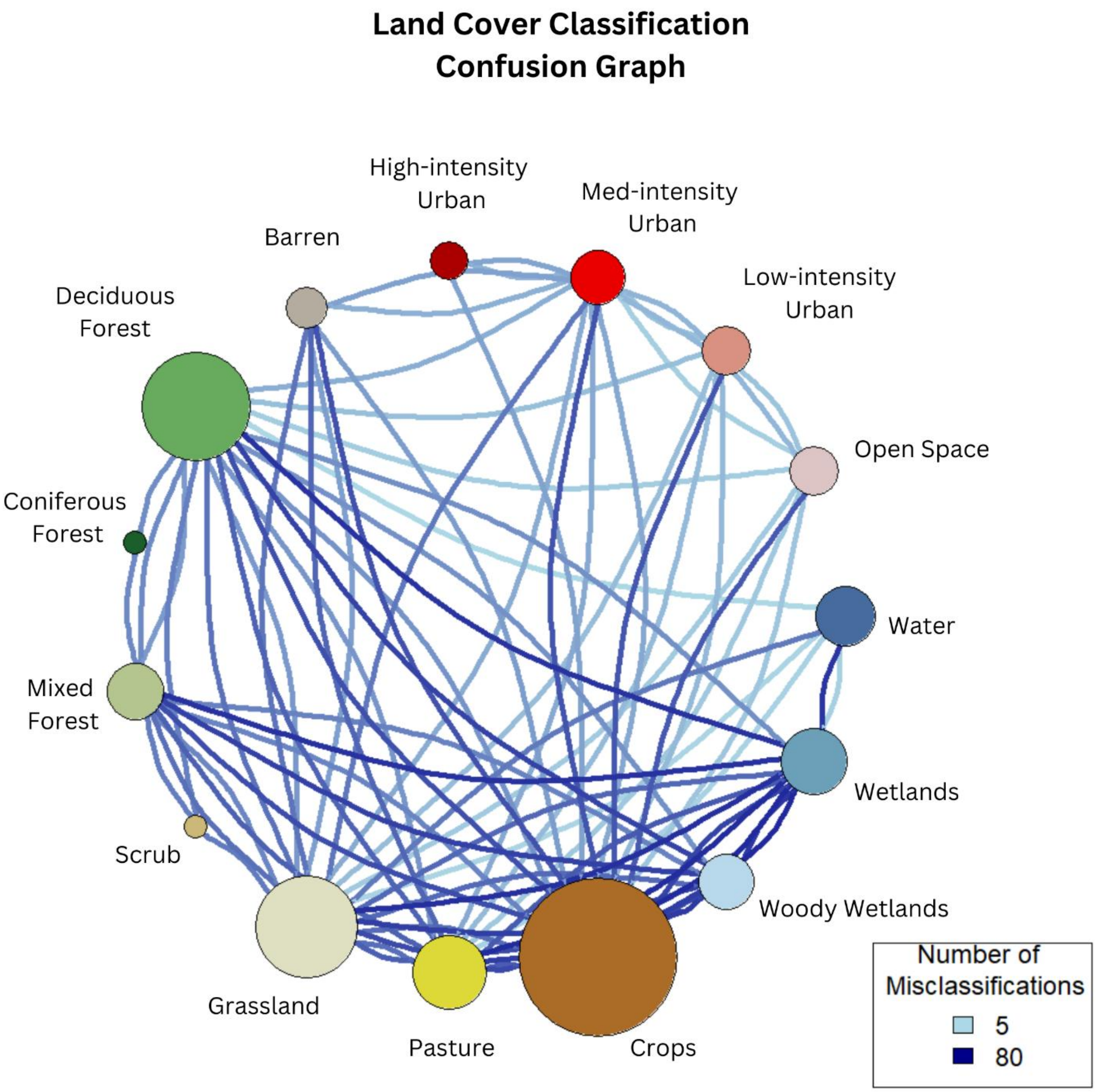


Figure 4. A network graph of the confusion matrix, with lines indicating misclassifications between categories out of approximately 7000 samples. The size of the circles indicates the number of samples from that category. It is clear that misclassification was most common between water and wetland areas along with a mixture of grassland, pasture, and crops.

The model exhibited high performance for my primary objective—differentiating permanent vegetation from other land-cover types to assess habitat connectivity. When reclassifying the multi-class output into a binary classification (permanent vegetation vs. non-permanent vegetation), the model demonstrated robust accuracy metrics (Table 1).

Test Accuracy	Predicted Positive	Predicted Negative
Actual Positive	1173.408669 (90.78%)	46.80185748 (3.56%)
Actual Negative	119.1950465 (9.22%)	1268.826625 (96.44%)

Training Accuracy	*Predicted Positive*	*Predicted Negative*
Actual Positive	2925.367284 (91.44%)	102.8364197 (3.22%)
Actual Negative	274.0246913 (8.56%)	3088.438272 (96.78%)

	MCC	**F_1**
Testing	0.874	0.934
Training	0.883	0.940

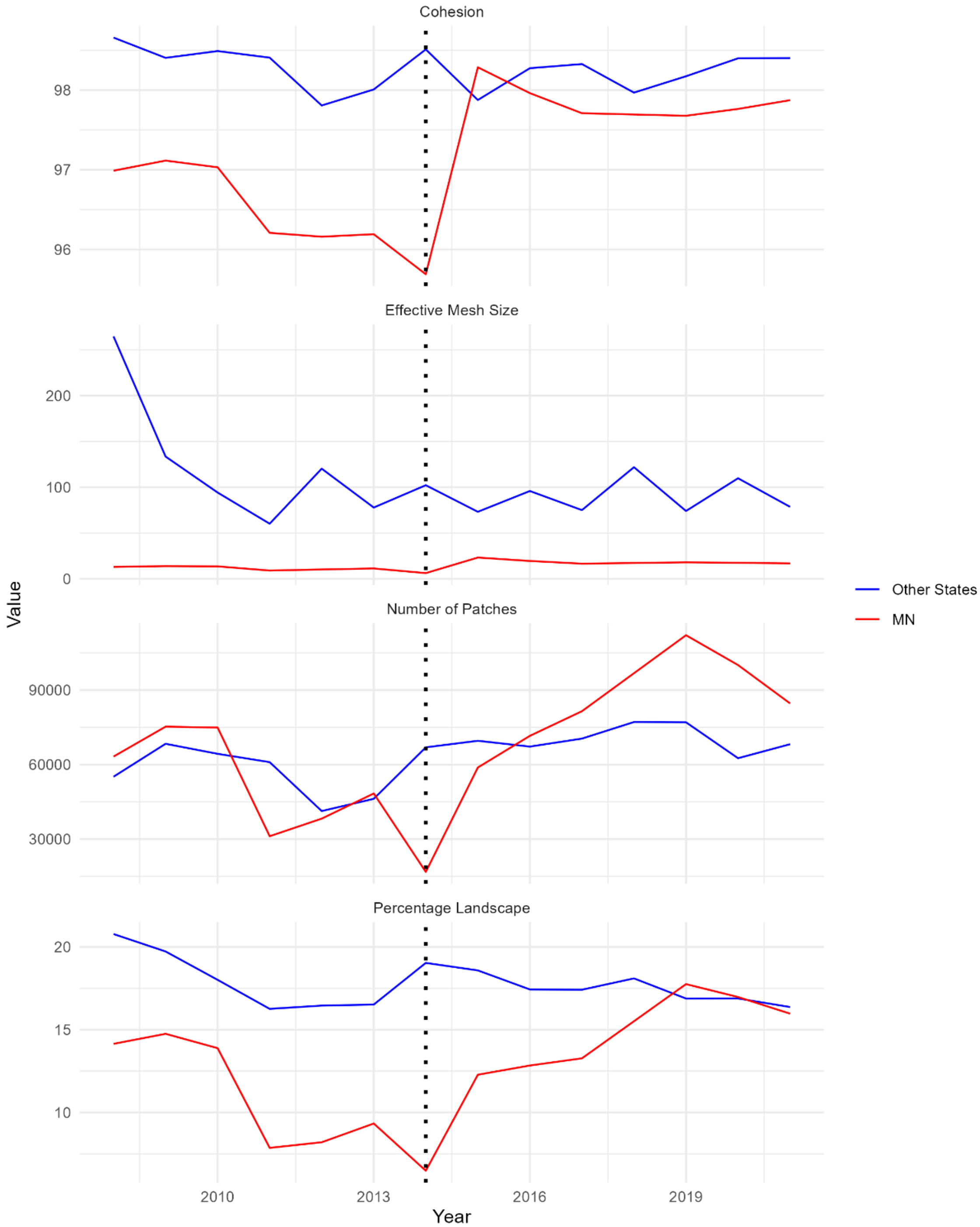
Table 1. Model accuracy on the binary classification between permanent vegetation and not permanent vegetation, summarized by MCC (Matthews Correlation Coefficient) and F_1 score.

The Matthews Correlation Coefficient (MCC), which provides a balanced measure of classification quality, was 0.874 for the test set and 0.883 for the training set. An MCC value close to 1 indicates excellent agreement between predicted and actual classes, supporting the reliability of the model (Chicco & Jurman, 2020). Similarly, the F_1-scores, which consider both precision and recall, were 0.934 for the test set and 0.940 for the training set. These high F_1-scores indicate that the model effectively identifies permanent vegetation while minimizing false positives and false negatives.

The model's false positive rate (FPR) for permanent vegetation was 8.5%-9%, which is better than the pre-established target threshold of 10%. A low FPR is crucial for accurately assessing connectivity because overestimating permanent vegetation could lead to an inflated perception of available resources. The false negative rate (FNR), representing the proportion of permanent vegetation misclassified as non-vegetation, was maintained below 4%, ensuring that truly vegetated areas were not overlooked.

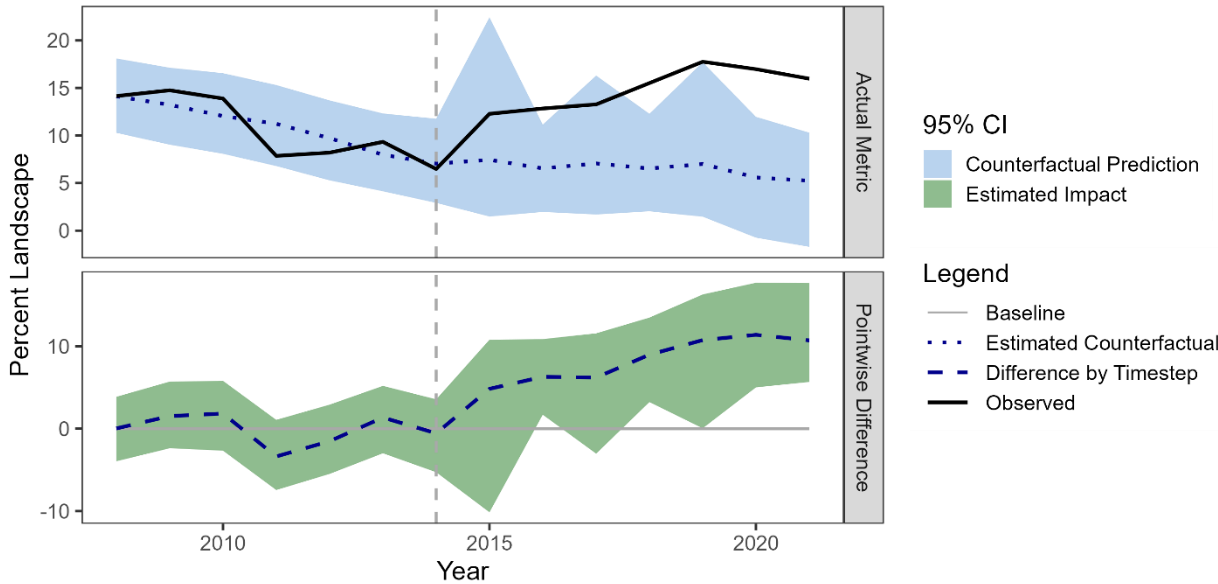
Structural Landscape Metrics

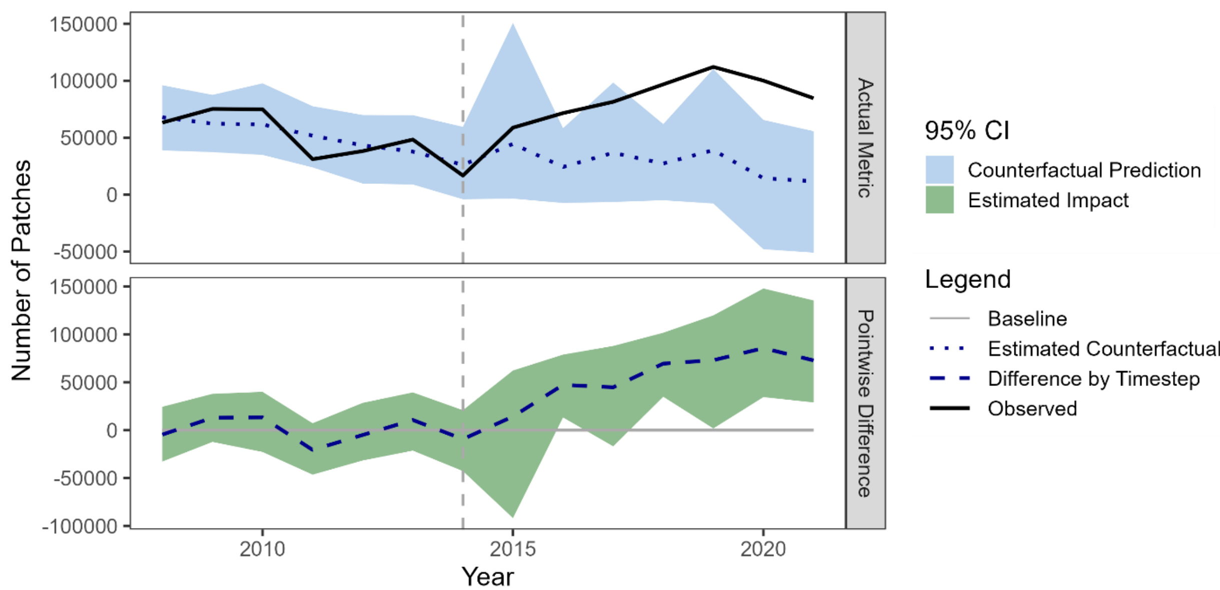
The classification process resulted in detailed land-cover maps for each year across the study period, which were processed with the landscapemetrics package for cohesion, effective mesh size, number of patches, and percent of the landscape (Fig. 5). With the exception of the number of patches, Minnesota tended to have lower values for all metrics, before and after the policy's implementation.



472 *Figure 5. Untransformed values for patch cohesion, effective mesh size, number of patches, and percentage of landscape between MN (treatment) and other states (control).*

Different trends emerged when Minnesota was compared to the synthetic control (Fig. 6). Significant impacts were detected in all metrics (including number of patches) indicating that the buffer law caused an increase in patch cohesion, mesh, number of patches, and percentage of landscape. Of particular note is that the model estimated an increase in patch cohesion by 2.19 units – a 2% increase ($p<0.001$, 95% CI: [1.59, 2.69]) – following the law's implementation (Fig. 6a). MN was higher in mesh by 10.74 units – a 149% increase ($p<0.001$, 95% CI: [7.03, 13.38], Fig. 6b). For number of patches, there was an effect of 58170 – a 86% increase ($p<0.001$, 95% CI: [29340, 83540], Fig. 6c) For percentage of landscape, the model calculated an effect of 12.63% ($p<0.001$, 95% CI: [7.43, 16.57], Fig 6d).


Percent Landscape
Actual Metric
Pointwise Difference
Year
2010
2015
2020
95% CI
Counterfactual Prediction
Estimated Impact
Legend
Baseline
Estimated Counterfactual
Difference by Timestep
Observed


Number of Patches
Actual Metric
Pointwise Difference
Year
2010
2015
2020
95% CI
Counterfactual Prediction
Estimated Impact
Legend
Baseline
Estimated Counterfactual
Difference by Timestep
Observed

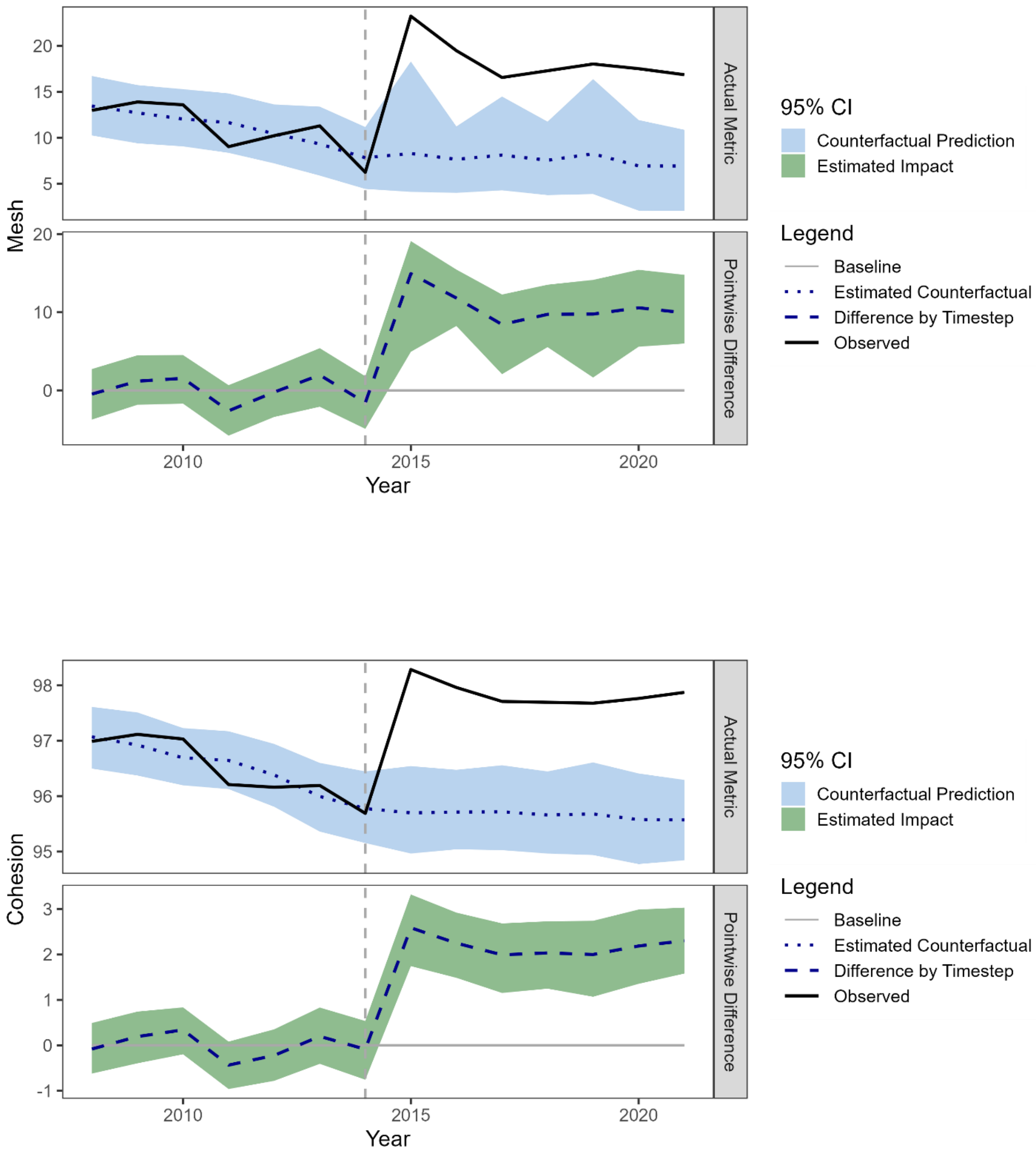


Figure 6. Synthetic controls for all landscape metrics. The solid line in the "original" rows represent the untransformed treatment values as in Fig. 5, compared to the dashed synthetic control prediction. The dashed line in the "pointwise" rows

represents the difference between the measured landscape metric and the predicted landscape metric at that time step, or the presumed difference in the metric due to the buffer law.

Two additional models were also run, focusing on the percentage of landscape consisting of permanent vegetation. One model was run with the classification map only being the areas affected by the buffer law (30m around streams and 15m around ditches) and the other model being the inverse – excluding all riparian areas. In the buffer strips, Minnesota showed an increase of 5.65% ($p=0.001$) permanent vegetation after 2015 compared to the synthetic control generated using the surrounding states. There was no increase ($p=0.011$) outside of the buffer strips (Fig. 7). For all models, the strongest predictor variable for connectivity was the acres of MN enrolled in the CRP that year (Fig.8). All other variables had a similar likelihood of inclusion at approximately 10%.

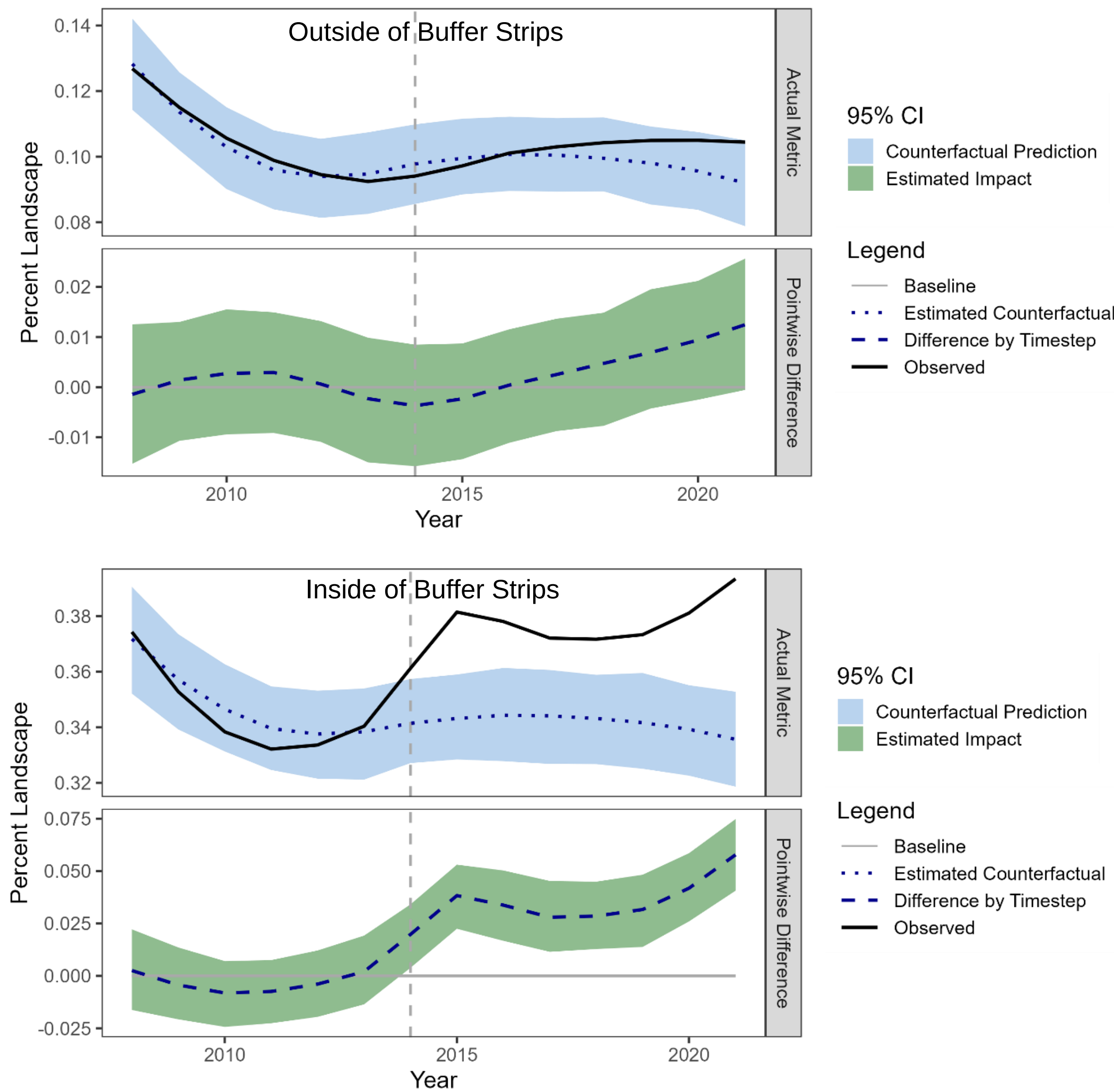


Figure 7. Synthetic controls for the percentage of landscape within buffer strips versus out of buffer strips, showing a significant increase inside the buffer strips, but staying

within the model's CI when only considering the landscape outside of buffer strips.

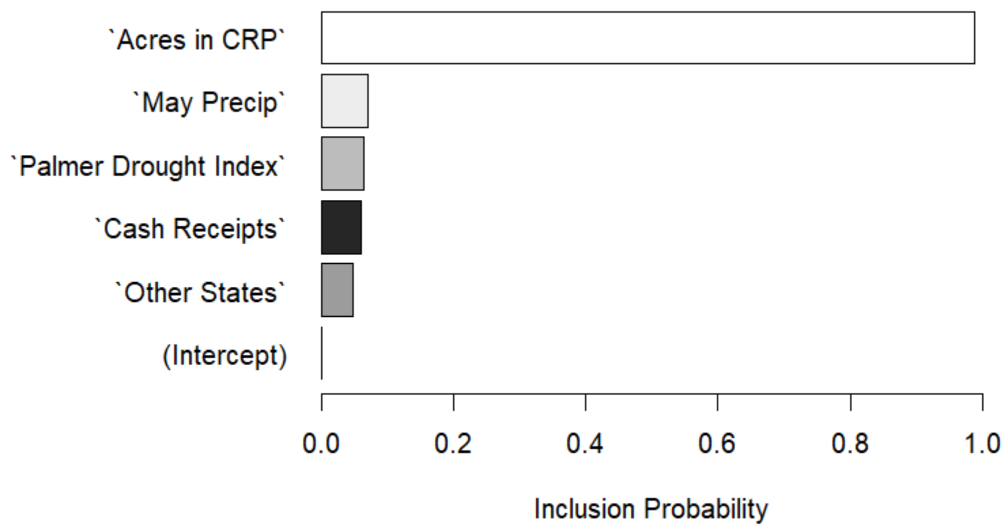


Figure 8. Inclusion probability for each included variable in the synthetic control model.

Circuitscape

The Circuitscape model showed a similar change (Fig. 9) when compared to the patch cohesion graph, with a moderate increase after the buffer law's passage. The average conductance prior to the law was 0.1430 and the latter conductance was 0.1643, a significant difference ($p<0.0001$). The sampled watershed was Fort Ridgely Creek (Fig. 10). This was not feasible to perform with a synthetic control, so no causal link was estimated.

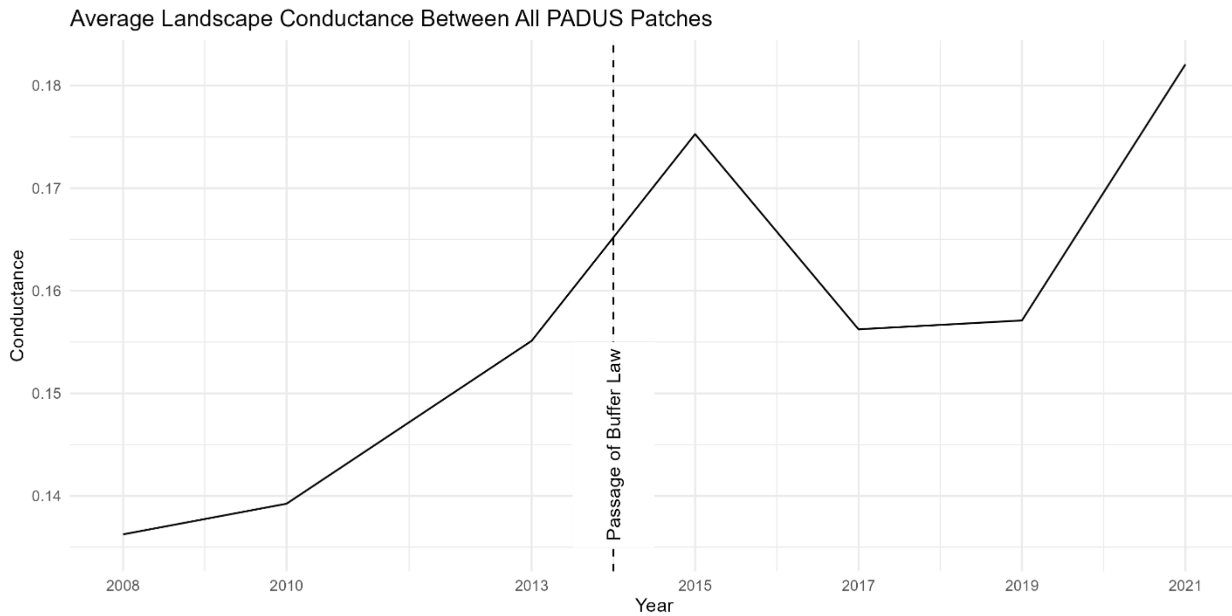


Figure 9. The average conductance between all PADUS patches for a randomly selected MN watershed by year.

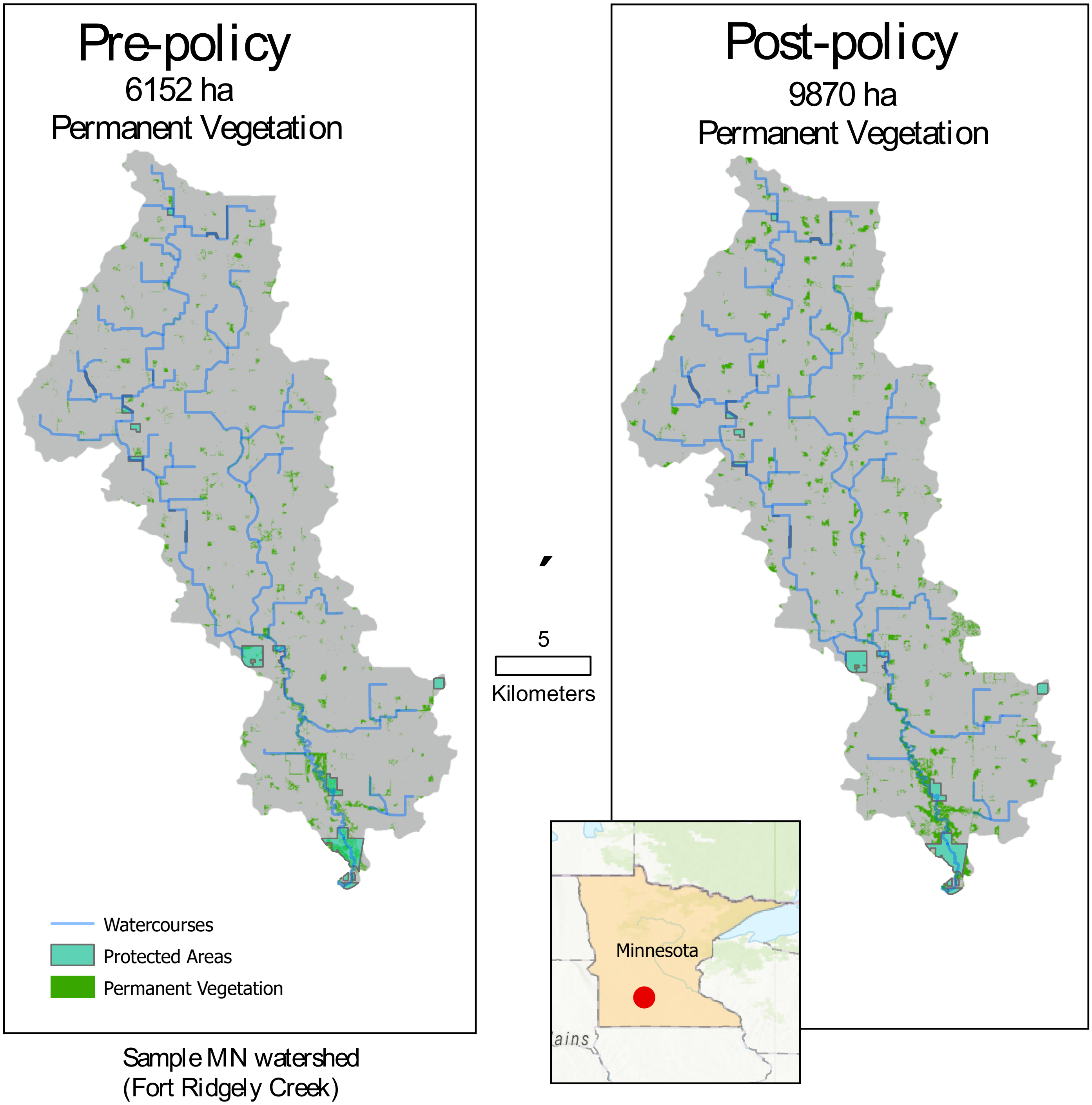


Figure 10. A sample watershed (Fort Ridgely Creek) in MN with a map of pre-buffer law (2011) and post-buffer law (2015), with about 50% more permanent vegetation post-implementation.

DISCUSSION

The analysis using landscape metrics and a synthetic control model revealed that Minnesota experienced notable increases in cohesion, effective mesh size, number of patches, and percentage of the landscape occupied by permanent vegetation following the implementation of the buffer law. Additionally, while it is difficult to estimate the direct effect on any particular species, the amount of improvement in patch cohesion, mesh, and percentage of the landscape are likely to be significant to many generalist species. The additional models using only inside buffer data and outside buffer data, respectively, found that the areas dictated by the law significantly affected the landscape and that the other areas did not. These findings suggest that the law was not only applicable to its primary goal of improving water quality but also conferred substantial co-benefits for wildlife conservation by enhancing landscape connectivity.

The increase in landscape cohesion and effective mesh size indicates that habitats in Minnesota have become more connected post-implementation of the buffer law. Improved connectivity facilitates the movement and dispersal of wildlife species, which is essential for maintaining genetic diversity, supporting recolonization, and reducing the risk of local extinctions (Brudvig et al., 2009; Haddad et al., 2015; Hanski, 1998). The increase in the number of patches, coupled with a higher percentage of the landscape covered by permanent vegetation, suggests that the buffer strips have created additional habitats that can serve as refuges or stepping stones for various species, particularly those with limited dispersal capabilities (Evans et al., 2014; Öckinger & Smith, 2007). Schumaker (1996) found that a patch cohesion increase from .96 to .98 could translate to an approximately 10% higher likelihood that an individual would have a successful dispersal between patches. This could include many insects, including pollinator species such as bees, flies, and butterflies (Cole et al., 2015; Dover et al., 2000; Jauker et al., 2009; Lintern et al., 2020). In the Corn Belt, this could even include endangered species such as the rusty patched bumblebee, which can be found in disturbed and edge areas that have sufficient resources (Ragan, 2021; U. S. Fish and Wildlife Service, 2016).

These enhancements in habitat structure are particularly meaningful in the context of the Corn Belt, where intensive agriculture has led to widespread habitat loss and fragmentation (Samson et al., 2004; Samson & Knopf, 1996). The buffer strips provide critical habitat features within the otherwise hostile agricultural matrix, potentially benefiting a range of taxa including arthropods, birds, reptiles, amphibians, and plants (Best et al., 1997; Brudvig et al., 2009; Cole et al., 2015; Damschen et al., 2019; Lukens et al., 2020). For instance, pollinator species, which are vital for both wild ecosystems and agricultural productivity, may find foraging and nesting opportunities within these buffer zones (Jauker et al., 2009; Ricketts et al., 2006; Zhang et al., 2023).

These findings also have important policy implications, providing empirical evidence that CAC environmental regulations, such as Minnesota's buffer strip law, can yield significant ecological benefits beyond their primary objectives. Considering all the potential impacts of agri-environmental policies becomes especially important in these instances. This is especially true of buffer strips, whose efficacy at water filtration has become more in doubt in recent years as studies find mixed results that are highly dependent on their exact placement in the landscape (Fleming et al., 2022; Lintern et al., 2020; Liu et al., 2023; Moody et al., 2023; Schilling et al., 2023). If buffer strips become less justifiable for water quality, it remains important to consider their other potential environmental effect.

Other states in the Corn Belt lacking similar legislation did not exhibit the same positive trends in habitat connectivity metrics, suggesting that voluntary or incentive-based conservation programs may not be as effective in achieving large-scale landscape changes. Quickly implemented CAC style policies may be largely contested in the short-term, but could have effects in swaying public opinion towards conservation in the long term (Khanal et al., 2022). CAC regulations can offer advantages over incentive-based approaches in managing agricultural landscapes, particularly when addressing environmental challenges that act on landscape scales, such as non-point source pollution or landscape connectivity. Ensuring uniform compliance can be more effective in achieving immediate and measurable environmental outcomes. While incentive-based policies may offer cost savings and flexibility to farmers, their effectiveness often depends on the willingness of participants and the adequacy of governmental financial resources, which can limit their scalability and long-term impact.

The successful application of a random forest classifier on high-resolution NAIP imagery demonstrates the viability of machine learning techniques in large-scale land cover analysis, even with the data limitations of NAIP. The high accuracy in distinguishing permanent vegetation demonstrates a valuable methodological approach and underscores the potential of integrating NAIP data, Landsat data, and cloud-based processing for segmentation and machine learning models for environmental research. Most past land cover classifications have been performed at coarse resolutions of 30m or more, limiting their application for fine-scale landscape change (Foody, 2002; Phiri & Morgenroth, 2017). Buffer strips, which could be as narrow as 5m, would be undetectable in most 30m pixels. On the other hand, previous implementations of high-resolution landcover classifications have been limited, restricted to small extents, insufficient accuracy, or low-resolution themes (Maxwell et al., 2019; Phiri & Morgenroth, 2017; Pierce, 2015; Prasai et al., 2021). The resultant code and model from this study could be effectively repurposed for many regions, especially if analyses were targeted at permanent vegetation surfaces. Similarly, the model was also highly accurate at determining impervious surfaces, opening multiple new avenues for research.

These findings support the notion that mandatory environmental policies can play a crucial role in reversing habitat fragmentation trends and promoting biodiversity conservation within private agricultural lands (Eichenwald et al., 2020). Policymakers in other agricultural regions may consider implementing similar regulations to address environmental challenges such as habitat loss, biodiversity decline, and ecosystem service degradation.

LIMITATIONS

A limitation of any synthetic control, like the one used in this study, is that the statistical method meant to isolate the causal effect of the buffer strip law may be insufficient. Supposing other significant, landscape-level changes occurred in MN around the same time as the buffer law and not in the remaining states, the buffer law would not have been sufficiently isolated. The measured impact would be partially caused by these other changes, rather than the buffer law alone. However, the null test on inside buffer strips versus out of them provides significant evidence that this is not the case.

Additionally, machine learning has inherent limitations to its accuracy. While the model was sufficiently accurate to meet the standards set before the analysis, any false positives or false negatives regarding permanent vegetation could strongly affect structural connectivity metrics, especially if they were experienced at different rates inside of Minnesota versus outside of it. Similarly, NAIP data is limited in its accuracy because it is gathered by inconsistent observers.

There is a significant assumption in referring to permanent vegetation as any type of "habitat." Habitat is typically defined as something that is extremely species-specific and "permanent vegetation" cannot be called "habitat" for any given species. The permanent vegetation classification includes a large diversity of ecological systems, even within the buffer strips themselves (since there are no major requirements on what they are planted with, besides plants that are permanently rooted and are not invasive). However, the matrix should not be overly discounted, especially when evaluated for its ability to facilitate connectivity between higher-quality patches or provide resources to generalist species. While difficult to pinpoint any one species benefitted by this policy, buffer strips are effective habitat for a diversity of species (Cole et al., 2015; Evans et al., 2014; Marczak et al., 2010; McCracken et al., 2012; Sirabahenda et al., 2020; von Königslöw et al., 2022).

Finally, while functional connectivity is typically well-correlated with the measurements of structural connectivity used in this study, no predictions of functional connectivity can be made for individual species. By only using structural connectivity as a measure of the law's impact, this study is limited from providing empirical evidence of any changes in functional connectivity, which should be addressed by future research.

FUTURE DIRECTIONS

The American Corn Belt remains ripe for agri-environmental policy research and this study will provide multiple opportunities for additional research. This type of evaluation is nonexistent in the literature and this scenario offers a valuable policy experiment. While this study estimated the land value of the area affected by the law, it did not estimate the actual opportunity costs of implementation. Additionally, I found non-monetized environmental benefits but cannot yet determine whether the policy passes a benefit-cost test. However, it passes the significance threshold of appearing to have a positive environmental impact, drawing the need for future research on such policies.

In the future, fieldwork could be conducted to gather empirical evidence of wildlife use of the buffer strips. For example, one could survey buffer strips for wildlife diversity and abundance in an agricultural region along a gradient of distances from protected areas. If done in multiple locations and states, I expect that distance from protected areas and diversity/abundance of wildlife will be more negatively correlated in states with less strict buffer laws and lower landscape connectivity. I expect this because wildlife should be more likely to penetrate intensive agricultural landscapes when more permanent vegetation is available and higher landscape connectivity (Cole et al., 2015; Öckinger & Smith, 2007; Ricketts et al., 2006).

Other research could include analyzing MN wildlife diversity/abundance trends versus those in other states. Using a similar synthetic control method, this research could attempt to isolate a causal relationship between the buffer law and increased diversity and abundance of wildlife, potentially providing further evidence that buffer strip laws provide habitat or dispersal corridors for wildlife. It would also be helpful to incorporate specific characteristics of each buffer strip to determine how this broad set of differences could impact wildlife, such as width, planting diversity, and type of surrounding agriculture. This would also help to determine which species were significantly affected by the law. Designing buffer strips with wildlife in mind would not only improve their effectiveness as wildlife resources (Gill et al., 2014; McCracken et al., 2012), but also impact their effectiveness at their main intent: maintaining water quality (Dunn et al., 2022).

Moreover, incorporating qualitative data on landowner compliance, attitudes, and management practices could provide insights into the social dimensions that influence the effectiveness of the buffer law. Understanding the challenges and objectives of farmers is crucial for designing policies that balance agricultural productivity with environmental sustainability and conservation. An essential part of agri-environmental policy is the management of farmer and other stakeholder attitudes and perceptions, which can be extremely heterogenous and hard to predict (Banerjee et al., 2021; Canales et al., 2023; Canessa et al., 2023; Le Coent et al., 2021), complicating the implementation of CAC policies. Additionally, the effects of conservation policies can differ drastically depending on their implementation, which can have many variables, such as the where, when, and how (Drechsler, 2023; Kuhfuss et al., 2022; Le Provost et al., 2022). However, these complications become less important when considering the value of a policy at a landscape scale across a whole state, maintaining the value of this study's results.

The results of this and future research could inform and improve the conservation and management of Minnesota's ecosystems and wildlife populations and help with the design and implementation of future buffer strip laws in other areas. The study could also inform future policies to reduce fragmentation of the state's ecosystems, improve habitat for the native biota, and reduce soil erosion and water pollution. Despite the limitations, the findings of this type of study can provide valuable insights into the impact of buffer strips on landscape connectivity and their potential benefits, serving as a model for future research that increases our understanding of how to preserve ecosystems and wildlife populations.

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