Grassland Assessment of North American Great Plains Migratory Bird Joint Ventures

A report prepared for ConocoPhillips

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***Project Partners*:**

Prairie Habitat Joint Venture, Prairie Pothole Joint Venture, Northern Great Plains Joint Venture, Rainwater Basin Joint Venture, Playa Lakes Joint Venture, Oaks and Prairies Joint Venture, Rio Grande Joint Venture, Sonoran Joint Venture, USDA Farm Services Administration

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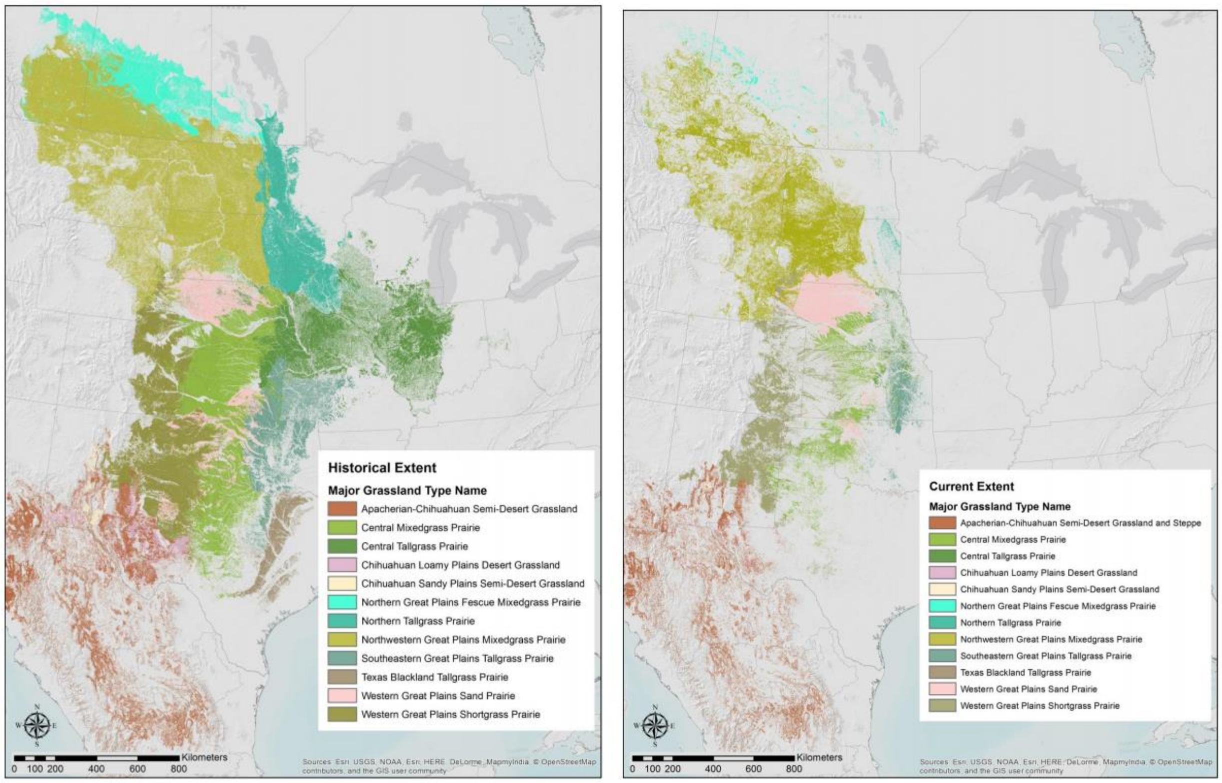
Abstract

Grassland loss and degradation has been extensive in the North American Great Plains and has resulted in a subsequent decline in biodiversity. The Prairie Pothole Joint Venture (JV) conducted a grassland assessment, in coordination with seven other North American Migratory Bird JVs within the Great Plains. The goal of this assessment was to provide explicit planning and conservation delivery datasets to assist JV partnerships to stem grassland losses and avian population declines. We used recent time-series landcover data to spatially identify potentially undisturbed lands (PUDL) defined as grass/shrub/wetland complexes with no history of agricultural cultivation or development. We conducted supervised classification using Sentinel-2 satellite data to further refine vegetation composition in the PUDL layer. Finally, we estimated grassland loss rates over time and compared those to grassland protection efforts. Within the collective JV boundaries, 51.13% of the area was comprised of PUDL, of which 3.71% was protected. The supervised classification indicated undisturbed grass made up the majority of the PUDL layer in all JVs except Rio Grande, which was dominated by shrubland. Undisturbed grass within the PUDL layer composed ~40-65% of the total grassland found in each JV, except in the Prairie Habitat and Prairie Pothole where estimates were ~25-30%. We estimated an average rate of grassland loss across all JVs in US and Canada of -0.98%/yr using annual time-series landcover datasets, and an average rate of grassland loss across all JVs in Mexico, US, and Canada of -0.23%/year using periodic time-series landcover datasets. Prairie Habitat and Prairie Pothole JVs had the smallest percentage of PUDL remaining (17.93% and 25.34% PUDL, respectively), with estimated undisturbed grassland loss rates more than doubling the collective joint venture averages. We estimated that in the next 10 years undisturbed grassland loss will be occurring on average ~7-25 times faster than protection when extrapolating current low and high estimates of grassland loss vs. a recent 10-year average annual estimate of grassland protection.

Introduction

North American temperate grasslands are considered the most threatened major ecosystem in the world when comparing ratios of habitat conversion to habitat protection across all major biomes (Hoekstra 2005). The North American Great Plains has sustained extensive grassland loss and degradation since the 1800s due to agriculture, urbanization, exotic plantings, afforestation, and loss or suppression of ecological drivers such as native free roaming grazers and fire (Knopf 1994, Samson et al. 2004, Brennan and Kuvlesky 2005, Askins et al. 2007). Historic grassland losses within temperate North America total approximately 70%, including complete conversion of the most productive areas where only remnant tracts remain (i.e., tallgrass prairie; Figure 1; Samson et al. 2004, Comer et al. 2018). Recent estimates of agricultural conversion and grassland protection in the Northern Great Plains suggest grassland loss is occurring five times faster than grasslands can be protected (Doherty et al. 2013).

Figure 1. Historic extent (Left) and current extent (Right) of 12 major temperate grassland types of the North American Great Plains (from Comer et al. 2018).



Land use intensification in the Great Plains has depleted the land of natural resources and disrupted ecosystem services. Grassland conversion to cropland increases the export of water, sediment, nitrogen, and phosphorous out of the region (Flynn et al. 2017). Pesticide use and a loss of ecologically relevant vegetation have caused biota such as arthropods and birds to decline, which also causes a decline in pollination and pest control services (Sauer et al. 2017, NABCI 2016, Sanchez-Bayo and Wyckhuys 2019).

Grassland birds are the fastest declining bird guild in North America, with 74% of grassland species in decline, and 53% of their population lost since the 1970’s (~700 million birds lost; Rosenberg et al. 2019). Grassland specialists, such as native endemic grassland birds of the Great Plains, are some of the fastest declining bird species in North America. For example, The North American Breeding Bird Survey has estimated McCown’s Longspur annual population decline is 5.90% since 1966, and has an estimated total population decline of 94% (Sauer et al. 2017, Rosenberg 2016). Like other endemic grassland species, McCown’s Longspur is specialized in utilizing a particular vegetation composition and structure, and has a breeding distribution within the Northern Great Plains of the US and Canada, and winters in southern US to the Chihuahuan grasslands of Mexico. Precipitous population declines of grassland specialists coupled with an annual-cycle geography that spans three nations necessitates transboundary partnerships and a concerted collaborative conservation approach to stem further grassland bird declines. Migratory Bird Joint Ventures (JV) are particularly well suited to deliver this conservation effort.

Migratory Bird JVs are collaborative, regional, public-private partnerships that conserve habitat for the benefit of priority bird species. JVs bring diverse partners together under the guidance of national and international bird conservation plans to design and implement landscape-scale conservation efforts. The North American Waterfowl Management Plan (NAWMP) established the first JVs (U.S. Department of the Interior and Environment Canada 1986). Additional JVs were subsequently created to collectively support NAWMP and three other bird management plans: the Partners in Flight Landbird Conservation Plan (Rosenburg et al. 2016), the United States Shorebird Conservation Plan (Brown et al. 2001), and the North American Waterbird Conservation Plan (Kushlan et al. 2002). Conservation delivery by JVs has helped protect, enhance, and restore nearly 27 million acres of habitat across North America. JVs have a long history of success in public and private collaboration and have leveraged 31 non-federal partner dollars for every federally appropriated dollar (National Joint Venture Communications, Education, and Outreach Team 2018)

Cooperation between JVs at larger scales (regional to continental) is only beginning to coalesce as JV networks realize the necessity of large scale planning and action for conservation of migratory birds across full annual-cycle geographies. JVs utilize the best science and data available to inform conservation delivery through decision support tools, such as spatial landcover assessments and trends, and species distribution models. JVs are also focused on filling information gaps to better understand what factors are inhibiting avian population growth. These tools are generally produced separately by each JV, and tools that cross JV boundaries are limited. Decision support tools that span full annual-cycle geographies would provide a robust approach to priority grassland-dependent bird conservation, with the identification and protection of undisturbed native grasslands being paramount. These lands offer greater ecosystem services than restored lands and play a critical role in meeting grassland bird needs (Dodds et al. 2008, Somershoe 2018). While perpetual protection is not the only conservation tool, it does represent a long-term commitment to protection and biodiversity that is easily measured and tracked through space and time (Dohery et al. 2013, Walker et al. 2013).

Our goal was to generate a transboundary grassland assessment across eight Great Plains JV administrative boundaries that can inform conservation planning across the full annual-cycle of migratory grassland-dependent birds. Our first objective was to spatially identify areas that are potentially undisturbed (i.e. lands that have never been tilled or developed) using time-series landcover data. The potentially undisturbed lands (PUDL) layer comprises areas of shrub, grass, or wetlands that have never been identified as cropland throughout the period of the time-series datasets used. Our second objective was to was to further refine the PUDL layer using remote sensing classification methods to identify major landcover classifications and two grassland types within the PUDL layer: those that are truly undisturbed and those that are disturbed (i.e., plowed/restored grasslands that were not captured as disturbed by the time-series landcover data). This geospatial data layer can serve as a companion to the PUDL layer to help direct protection, enhancement, or restoration efforts. Our final objective was to estimate the amount of PUDL already protected, as well as estimate grassland loss and protections rates. These data allow the creation of timeline projection scenarios of grassland loss and protection for the PUDL layer that will enable JVs to create conservation goals and understand the scale at which conservation must be delivered to meet those goals.

Methods

Study area

Our study area represented the administrative boundaries of the following JVs: Prairie Habitat, Prairie Pothole, Northern Great Plains, Rainwater Basin, Playa Lakes, Oaks and Prairies, Rio Grande, and the Mexico portion of Sonoran (Figure 2; DOI 2017). This study extent generally coincides with the North American Great Plains ecoregion and encompasses approximately 920.58 million acres from Canada to Mexico. This area is composed of relatively flat topography, with some topographic relief in the form of mountains, hills, table lands, buttes, and river drainages. Climate, grazers, and fire were the major ecological drivers in this region. Currently, native grazers have largely been replaced with cattle and fire is often suppressed. Precipitation generally increases from west to east, and average temperature increases from north to south. The region is prone to high winds, drought, and frost. Predominant land cover types in this region include croplands and grasslands with various compositions of shrub and wetland communities. Shrublands start to dominate the region in the southern expanse, and sagebrush becomes more common in the Northern Great Plains JV. Wetlands formed from glacial depressions (prairie potholes) are a common feature in the north, wind scoured playa wetlands are scattered across the southern portion of the geography, and rivers bisect the landscape throughout. Croplands are most prevalent in the northern/eastern portion of the Great Plains, and extend southwest into Kansas and northern Texas. Past analysis has shown grassland loss has been extensive throughout the region and loss rate estimates vary spatially and temporally (Table 1).

Figure 2. Study area consisting of eight North American Migratory Bird Joint Venture administrative boundaries.

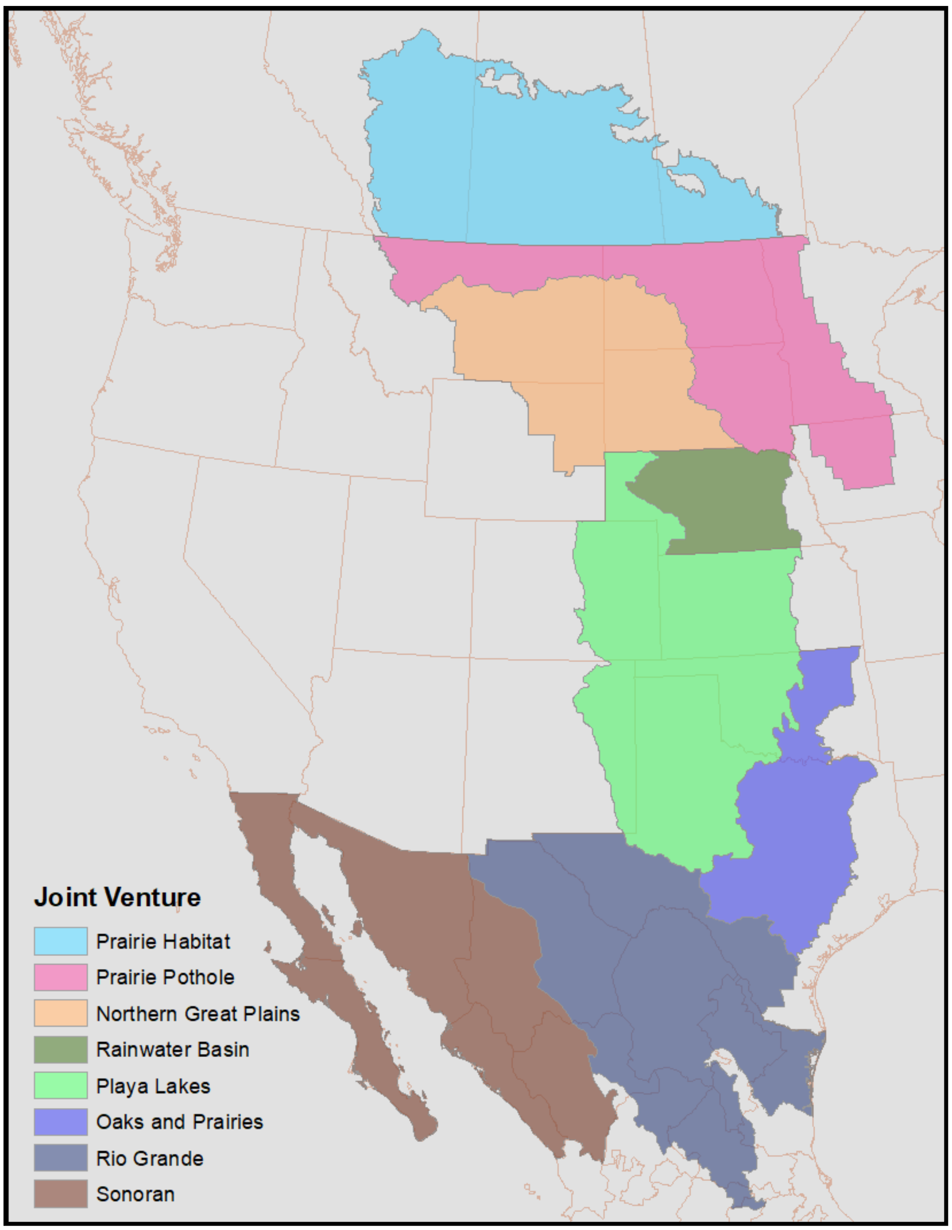


Table 1. Summary table of published regional grassland conversion rates in the North American Great Plains.

Region	Grass type	Time period	Annual Change Rate	Reference
Canadian PPR	Undisturbed	1985-2001	-0.62%	Watmough and Schmoll 2007
Canadian PPR	Undisturbed	2001-2011	-0.42%	Watmough et al. 2017
North Dakota	Undisturbed	1989-2003	-0.4%	Stephens et al. 2008
North Dakota and South Dakota	Undisturbed	1979-1997	-1.30%	Rashford et al. 2010
Northern Great Plains	Undisturbed	1997-2007	-0.10%	Claassen et al. 2011
Canadian PPR	All grass	1985-2001	+1.93%	Watmough and Schmoll 2007
Canadian PPR	All grass	2001-2011	+ 1.0%	Watmough et al. 2017
Western Corn Belt	All grass	2006-2011	-1.0%--5.4%	Wright & Wimberly 2013
U.S. PPR	All grass	1997-2009	-0.22%	Dahl 2014
Chihuahua	All grass	2006-2011	-1.22%	Pool et al. 2014
CONUS	All grass	2008-2012	-5.7M acres (all grass), -1.6M acres (undisturbed)	Lark et al. 2015
Great Plains	All grass	2009-2015	-2%	Gage et al. 2016
Eastern Dakotas	All grass	2004-2014	-0.43%	Wimberly et al. 2017
CONUS	All grass	2008-2012	-4.2M acres (all grass), -3.6M acres (undisturbed)	Wright et al. 2017

PUDL Layer

Our spatial analysis methods were informed by past work that identified potentially undisturbed lands in portions of the Great Plains. We used a similar deductive approach and data sources as Gage et al. (2016), who utilized classified remote sensing data, and the work of Bauman et al. (2016) and Lark et al. (2017) who used a proprietary vector dataset. Our general deductive approach iteratively removed different landcover classes from our study region (i.e., erased vector data or masked raster data). We first removed cumulative cropland derived from time-series landcover data. Cumulative cropland is defined as any area ever identified as cropland over the period of the time-series dataset despite any other classifications it may have had (i.e. does not include restored grasslands, such as CRP). We used vector datasets to erase areas where roads, railroads, or large water bodies (> 40 ac) occurred. Lastly, we removed barren, developed, and forested areas using the most current landcover datasets at the time of analysis. The remaining PUDL layer should include mostly grass, shrubs, and small wetlands; however given the temporal limitations and difficulties in landcover classification (e.g., classification at coarse resolutions and high error rates for some classes) we recognize that the PUDL layer includes other cover classes.

While our methods and results are similar across national boundaries, the datasets we used to derive estimates of PUDL are not. Datasets that represent landcover or land use are limited spatially and temporally. Spatial limitations are related to the national context of the funding source used for landcover projects. Temporal limitations occur because of the recency of development and deployment of remote sensing technology used to derive landcover data. See Appendix A for a detailed description of the datasets used and the geospatial workflow to obtain a PUDL layer for each country and Appendix B for landcover codes used in each dataset to create the PUDL layer.

Supervised Classification

We classified the landcover within our study region, excluding Sonoran JV due to time constraints. Classification was conducted to better define the landcover within the PUDL layer. This enabled the identification of cropland that was not identified by the landcover datasets we used to develop the PUDL layer. In addition, it provided classifications for Undisturbed grass, disturbed grass, and shrub at a 10 m resolution, which will serve as a useful companion dataset to the PUDL layer and a useful decision support tool for conservation.

We used supervised classification of remote sensing data in Google Earth Engine with a Random Forest classifier to conduct landcover classification (Gorelick et al. 2017, Breiman 2001). Google Earth Engine is a cloud-based platform for earth science analysis that hosts petabytes of geospatial data, an API and tools for analysis, and multiple machines that run processes in parallel for quick and efficient computation. Random Forest is an ensemble machine learning algorithm that classifies categorical response variable by generating decision trees from training data, partitioning the data and aggregating predictions to improve model fit and increase predictive performance.

We classified seven landcover types using data extracted at reference points from six covariates derived from Sentinel-2 Level-1C data and one topographic covariate from a Multi-scale Topographic Position Index (MTPI). Landcover classes included open water, developed/bare, forest, shrub, crop, and two classifications of grassland: potentially undisturbed and disturbed. See Appendix A for more detail on training data, and model tuning and validation. See appendix B for google earth engine programming code

Loss vs. Protection

Similar to methods used by Doherty et al. (2013), we estimated annual rates of grassland loss versus protection for grassland, shrubland, and wetland complexes in each JV. We obtained loss rate estimates using multiple time-series landcover datasets, and we obtained protection rate estimates, and the amount of PUDL currently protected, using protected land layer datasets. We projected those rates into the future to understand what scale of conservation is needed to meet conservation goals under different loss vs. protection rate scenarios. Scenarios included low to high estimates of landcover change, recent 10-year average annual protection rate, and the recent 10-year annual average protection rate doubled and halved. We used the International Union for the Conservation of Nature's (IUCN) definition of protection to identify protected lands (UNEP-WCMC and IUCN 2018). The IUCN defines protected lands as "…clearly defined geographical space, recognized, dedicated and managed, through legal or other effective means, to achieve the long-term conservation of nature with associated ecosystem services and cultural values." Grassland loss rates are based on the amount of grasslands tilled or developed over time. We used a 10-year annual average protection rate for all grasslands to illustrate what is possible for PUDL protection if conservation efforts were focused on these lands. See Appendix A for detailed methods and Appendix B for programming code used to derive loss rate estimates.

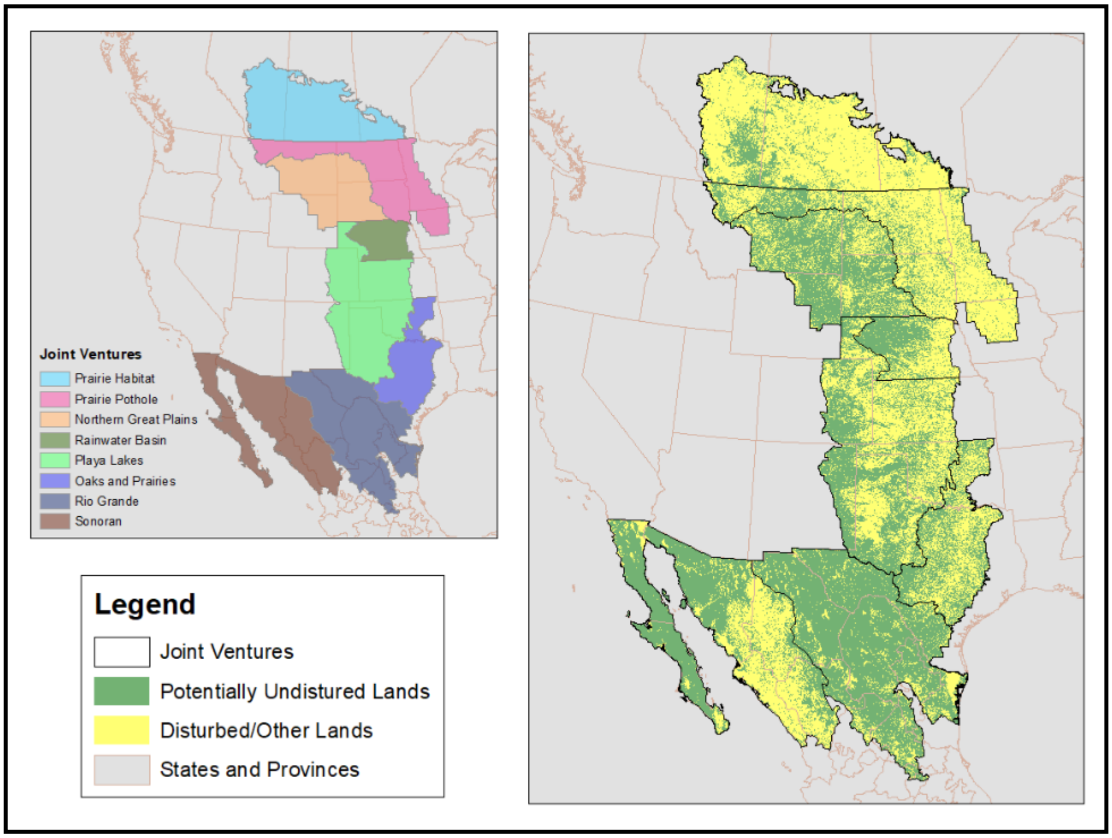
Results

PUDL Layer

The tri-national PUDL estimate represented 51.13% of our study area (470.73 million acres; Figure 3, Table 2). Lands with a history of cultivation represented 37.62% of the region, and an addition 11.25% of the region represented area that were developed, bare, forested, or large water bodies. PUDL estimates were greater in western and southern regions, which contained less arable land. The Rio Grande, Sonoran, Playa Lakes, and Northern Great Plains JVs had higher PUDL estimates than the other joint ventures, with 138.41, 80.25, 79.69, and 64.13 million acres, respectively. These estimates represented 83.91%, 57.20%, 49.91%, and 68.28% of each JV, respectively. The Oaks and Prairies, Prairie Pothole, Prairie Habitat, and Rainwater Basin had smaller PUDL estimates, containing 33.70, 29.96, 25.31, and 19.23 million acres, respectively. These estimates represented 49.83%, 25.34%, 17.93%, and 55.52% of each JV, respectively (Figure 3, Table 2).

Figure 3. Potentially undisturbed lands (PUDL) within eight Migratory Bird Joint Ventures of the Great Plains region. Figure A) depicts the spatial extent of the PUDL layer and B) summarizes the amount of PUDL cover in each joint venture.

A)



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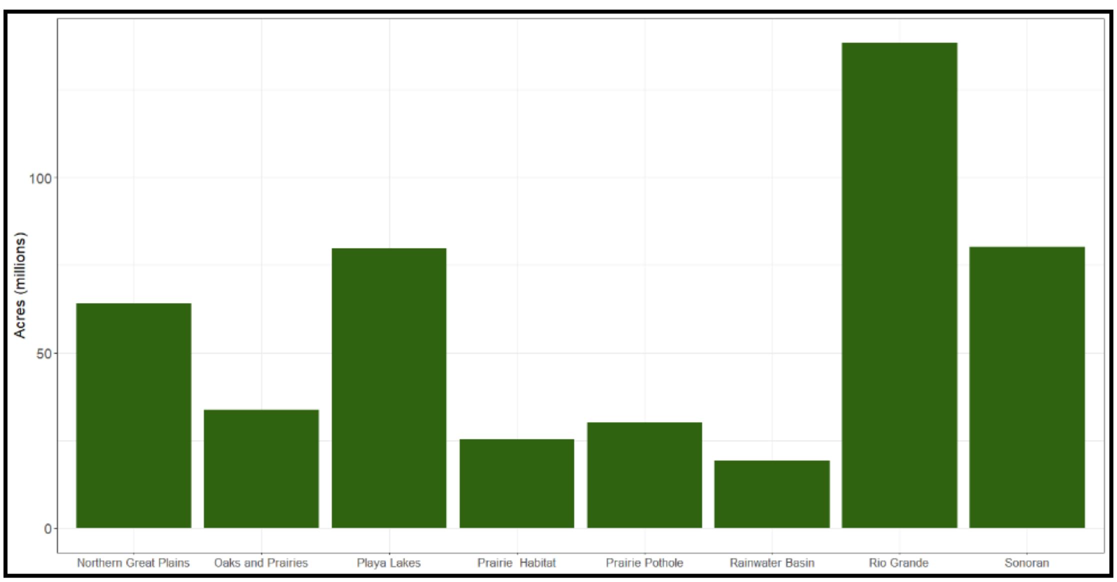


Table 2. Potentially undisturbed lands (PUDL) were spatially identified throughout eight Migratory Bird Joint Venture. This table provides summary statistics for the amount of cumulative cropland acres removed, potentially undisturbed lands (PUDL), the amount of protected PUDL, the percent PUDL within each joint venture, and the percentage of protected PUDL with each JV's PUDL layer.

Joint Venture	Joint Venture Acres	Cumulative Cropland Acres	PUDL Acres	Protected PUDL Acres	Percent PUDL	Percent PUDL Protected
Prairie Habitat	141,170,695.00	118,660,606.34	25,317,401.51	4,829,541.66	17.93	19.08
Prairie Pothole	118,258,082.85	77,705,570.60	29,965,848.02	2,092,189.00	25.34	6.98
Northern Great Plains	93,932,951.64	19,366,918.59	64,134,414.28	566,656.15	68.28	0.88
Rainwater Basin	34,648,368.63	13,680,460.95	19,236,558.80	259,454.15	55.52	1.35
Playa Lakes	159,680,533.74	69,350,524.98	79,697,024.79	949,563.59	49.91	1.19
Oaks and Prairies	67,632,495.84	13,549,205.67	33,704,557.96	241,595.94	49.83	0.72
Rio Grande (USA)	37,468,580.21	1,812,300.88	32,915,094.62	1,255,690.37	87.85	3.81
Rio Grande (MEX)	127,483,822.83	16,511,743.44	105,503,089.94	8,130,333.58	82.76	7.71
Rio Grande (All)	164,952,403.04	18,324,044.31	138,418,184.56	9,386,023.95	83.91	6.78
Sonoran	140,303,734.37	15,683,358.61	80,251,251.68	15,731,374.97	57.20	19.60
All	920,579,265.11	346,320,690.05	470,725,241.60	34,056,399.41	51.13	7.23

Supervised Classification

Supervised classification accuracy assessment based on out-of-bag error indicated that model accuracy was lower in the west and southern regions (Table 3). Overall accuracy was 78.90% and ranged from 75.52% - 83.70% across the joint ventures. Grass and shrub classifications were the poorest performing classes with accuracy ranging from 54.40% to 77.31%. If the two grass classes were combined into one grass class, overall total accuracy rates for the JVs had an average improvement of 4.95% indicating that much of the misclassification occurred between the two grass classifications. While we report statistics for these covers within the PUDL layer, we acknowledge confidence in these estimates are low.

Table 3. Estimated out-of-bag accuracy rates from random forest classification models used to classify seven landcover types using 2016-2018 Sentinel-2 remote sensing data across the ecoregions of seven Migratory Bird Joint Ventures: Prairie Habitat (PHJV), Prairie Pothole (PPJV), Northern Great Plains (NGPJV), Rainwater Basin (RBJV), Playa Lakes (PLJV), Oaks and Prairies (OPJV), and Rio Grande (RGJV).

JV	Class	PUDL Grass	Disturbed Grass	Developed/ Bare	Water	Crop	Shrub	Forest	N	Accuracy
PHJV	PUDL Grass	596	140	8	0	19	37	0	800	74.50
PHJV	Disturbed Grass	133	543	2	0	68	66	13	825	65.82
PHJV	Developed/ Bare	39	4	625	2	23	1	0	694	90.06
PHJV	Water	3	9	7	654	6	7	4	690	94.78
PHJV	Crop	25	58	36	1	811	19	9	959	84.57
PHJV	Shrub	34	63	2	4	21	500	106	730	68.49
PHJV	Forest	3	16	1	3	4	124	619	770	80.39
PHJV	**Total**								**4,348/5,468**	**79.52**
PPJV	PUDL Grass	487	120	14	0	3	32	0	656	74.24
PPJV	Disturbed Grass	108	469	2	0	33	78	5	695	67.48
PPJV	Developed/ Bare	16	2	543	9	3	1	0	574	94.60
PPJV	Water	1	0	10	570	1	2	2	586	97.27
PPJV	Crop	13	26	6	0	699	22	16	782	89.39
PPJV	Shrub	24	69	1	1	12	444	74	625	71.04
PPJV	Forest	0	1	0	2	10	60	516	589	87.61
PPJV	**Total**								**3,728/4,507**	**82.72**
NGPJV	PUDL Grass	471	83	23	0	16	93	3	689	68.36
NGPJV	Disturbed Grass	96	348	2	0	58	67	1	572	60.84

NGPJV	Developed/ Bare	37	8	414	7	4	16	4	490	84.49
NGPJV	Water	1	2	8	474	0	2	3	490	96.73
NGPJV	Crop	39	53	9	0	440	4	0	545	80.73
NGPJV	Shrub	122	66	13	2	2	389	60	654	59.48
NGPJV	Forest	0	4	2	1	0	51	478	536	89.18
NGPJV	**Total**								**3,014/3,976**	**75.80**
RBJV	PUDL Grass	368	75	14	0	4	15	0	476	77.31
RBJV	Disturbed Grass	77	291	2	1	24	55	30	480	60.63
RBJV	Developed/ Bare	12	1	384	0	0	1	2	400	96.00
RBJV	Water	0	5	3	398	1	1	0	408	97.55
RBJV	Crop	9	21	0	0	370	0	0	400	92.50
RBJV	Shrub	15	38	2	0	0	314	43	412	76.21
RBJV	Forest	0	6	1	0	0	29	375	411	91.24
RBJV	**Total**								**2,500/2,987**	**83.70**
PLJV	PUDL Grass	727	160	36	0	38	146	0	1107	65.67
PLJV	Disturbed Grass	178	583	2	0	44	138	9	954	61.11
PLJV	Developed/ Bare	29	6	694	14	2	27	3	775	89.55
PLJV	Water	0	1	14	753	0	6	1	775	97.16
PLJV	Crop	84	54	13	0	775	14	0	940	82.45
PLJV	Shrub	173	141	11	1	11	672	57	1066	63.04
PLJV	Forest	0	8	1	1	0	52	713	775	92.00
PLJV	**Total**								**4,917/6,392**	**76.92**
OPJV	PUDL Grass	525	60	20	0	3	68	4	680	77.21
OPJV	Disturbed Grass	84	304	0	0	23	36	0	447	68.01

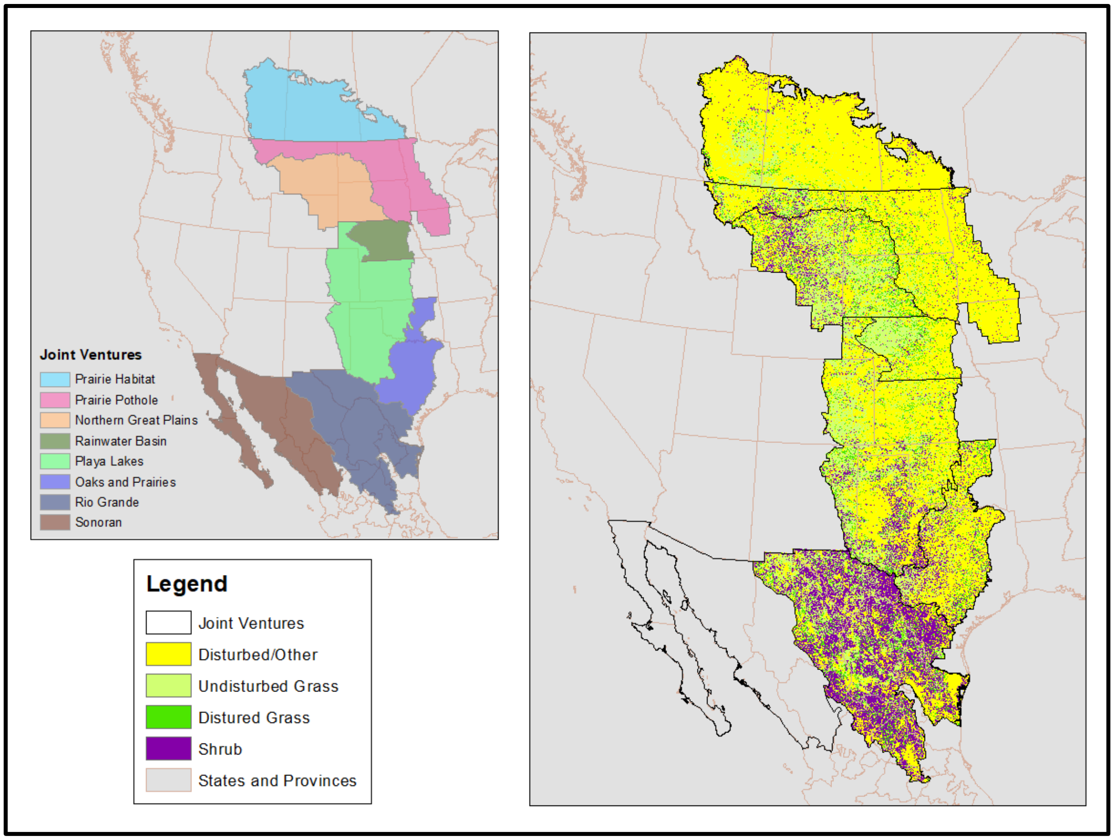
OPJV	Developed/ Bare	20	1	393	6	2	4	4	430	91.40
OPJV	Water	0	0	3	426	1	0	0	430	99.07
OPJV	Crop	15	26	5	0	401	5	0	452	88.72
OPJV	Shrub	84	24	4	0	6	470	63	651	72.20
OPJV	Forest	10	1	3	0	0	75	492	581	84.68
OPJV	**Total**								**3,011/3,671**	**82.02**
RGJV	PUDL Grass	513	167	82	2	22	157	0	943	54.40
RGJV	Disturbed Grass	166	520	4	4	148	97	3	942	55.20
RGJV	Developed/ Bare	44	8	687	7	2	52	0	800	85.88
RGJV	Water	2	3	13	750	0	19	9	796	94.22
RGJV	Crop	14	150	3	0	693	22	4	886	78.22
RGJV	Shrub	113	88	23	8	11	845	48	1136	74.38
RGJV	Forest	0	2	0	5	6	37	759	809	93.82
RGJV	**Total**								**4,767/6,312**	**75.52**
All	PUDL Grass	3687	805	197	2	105	548	7	5351	68.90
All	Disturbed Grass	842	3058	14	5	398	537	61	4915	62.22
All	Developed/ Bare	197	30	3740	45	36	102	13	4163	89.84
All	Water	7	20	58	4025	9	37	19	4175	96.41
All	Crop	199	388	72	1	4189	86	29	4964	84.39
All	Shrub	565	489	56	16	63	3634	451	5274	68.90
All	Forest	13	38	8	12	20	428	3952	4471	88.39
All	**Total**								**26,285/33,331**	**78.86**

We estimated 50.04% of our study region, excluding the Sonoran JV, is composed of potentially undisturbed lands (390.47 million ac). Supervised classification results indicated that the PUDL layer in this region is composed of 21.15% undisturbed grass (165.00 million acres), 15.56% shrub (121.41million acres), 8.41% disturbed grass (65.65 million acres), and 4.92% other cover types (i.e. crop, forest, etc.; 38.38 million acres; Figure 4, Table 4). Shrub was the dominate cover class in Rio Grande JV's PUDL layer and was a considerable component in Oaks and Prairies, Playa Lakes, and Northern Great Plains joint ventures. Undisturbed grass made up the largest component of the PUDL layer in every JV except Rio Grande. The largest amounts of undisturbed grass in the PUDL layer were in the Playa Lakes, Northern Great Plains, and Rio Grande JV (44.59, 35.78, 33.08 million acres, respectively). The remaining JVs all have similar amounts of undisturbed grass within their PUDL layers (range: 12.05-13.84 million acres).

Supervised classification indicated that Playa Lakes JV had the highest amount of total grass (undisturbed grass and disturbed grass combined both within and outside the PUDL layer; 88.76 million acres), with 50.24% being classified as undisturbed grass contained within the PUDL layer (Figure 5). Rio Grande and Northern Great Plains JV had similar estimates of 59.39 and 60.06 million acres total grass, with 55.69% and 59.58% being undisturbed grass in the PUDL layer, respectively. Prairie Habitat and Prairie Pothole JVs had similar estimates of total grass with 54.71 and 41.84 million acres, but only 25.31% and 29.32% of that was classified as undisturbed grass within the PUDL layer, respectively. Rainwater Basin and Oaks and Prairies JVs has the smallest estimates of total grass with 20.67 and 30.83 million acres, and 64.75% and 39.10% being classified as undisturbed grass within the PUDL layer, respectively.

Figure 4. Landcover classification derived from Sentinel-2 remote sensing imagery at a 10m resolution, depicted and summarized within potentially undisturbed lands (PUDL) layer. Figure A depicts the spatial extent of grass and shrub classes within the PUDL layer, and Figure B summarizes all different landcover within the PUDL layer for seven Migratory Bird Joint Ventures.

A)



B)

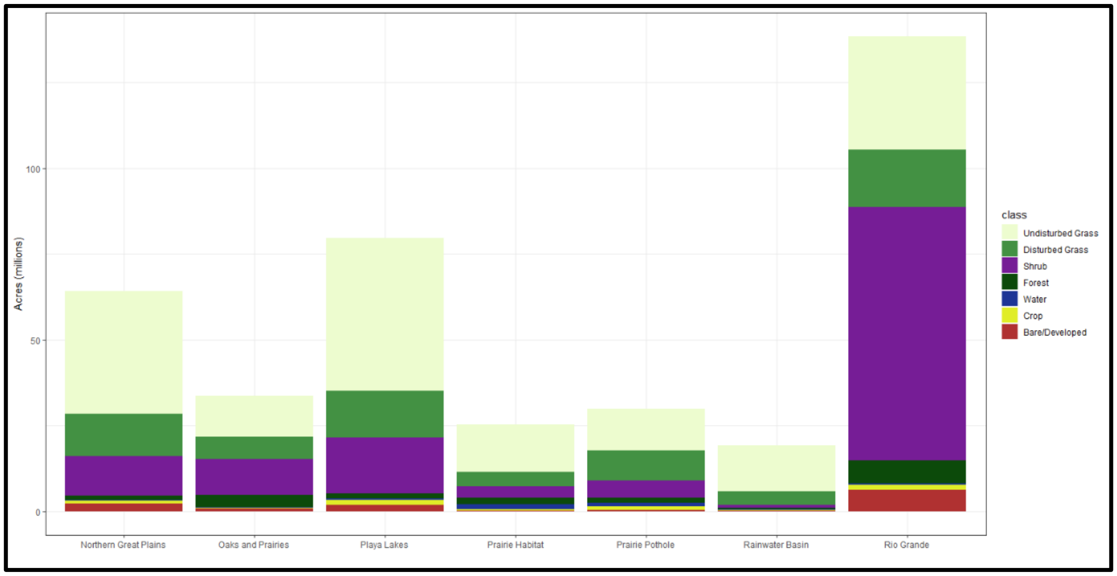
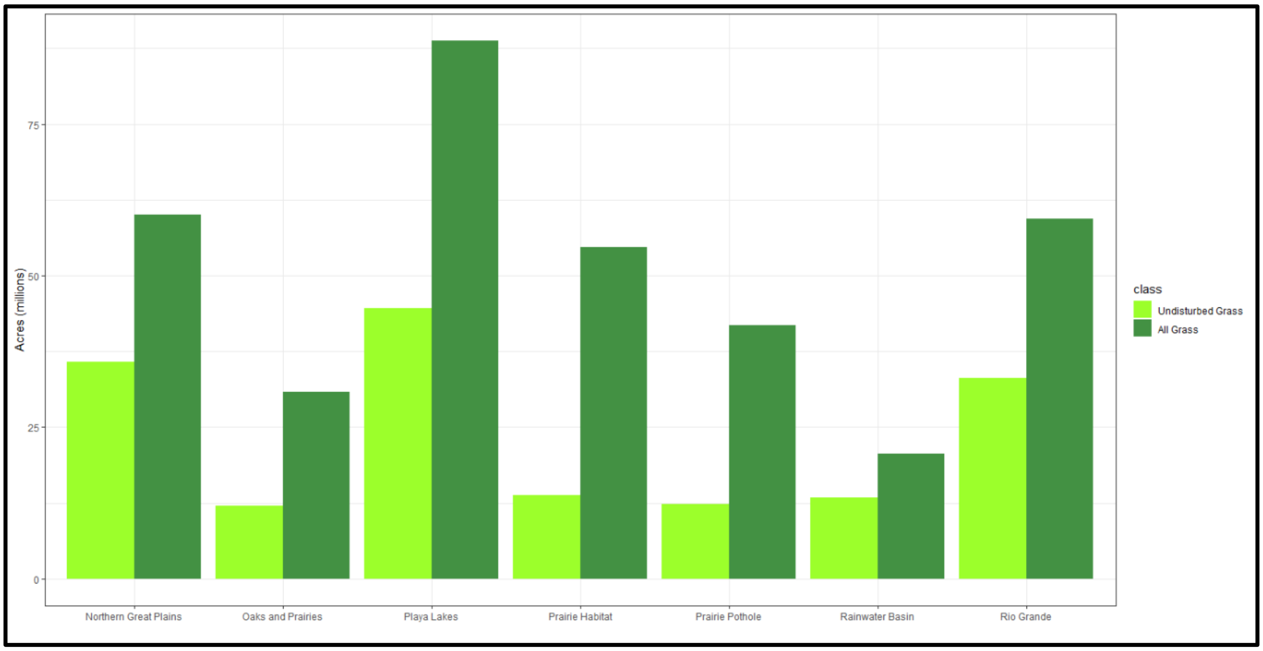


Table 4. Summary of supervised classification landcover (acres) within the PUDL layer, and all grass cover within each joint venture boundary (i.e., undisturbed grass and disturbed grass classifications both inside and outside the PUDL layer).

	PUDL Acres							All Acres
Joint Venture	**Undisturbed Grass**	**Disturbed Grass**	**Developed/Bare**	**Water**	**Crop**	**Shrub**	**Forest**	**Grass**
PHJV	13,848,864.39	4,213,348.21	206,028.14	1,533,425.97	301,148.54	3,297,428.72	1,890,487.06	54,714,439.03
PPJV	12,273,444.56	8,717,159.43	488,883.48	1,060,996.62	935,363.44	5,027,739.11	1,461,928.43	41,848,001.06
NGPJV	35,785,204.62	12,182,314.16	2,193,826.38	241,802.10	971,211.58	11,523,062.31	1,232,578.40	60,066,243.96
RBJV	13,355,708.34	3,988,661.00	166,636.89	163,038.20	186,439.68	914,223.83	461,575.49	20,627,115.62
PLJV	44,599,309.60	13,499,891.81	1,868,889.22	262,521.44	1,520,077.21	16,431,757.96	1,519,034.50	88,768,825.17
OPJV	12,056,417.35	6,357,063.11	706,859.57	341,643.05	272,080.17	10,488,130.08	3,482,947.20	30,830,532.48
RGJV	33,080,857.95	16,694,229.26	6,178,750.61	444,315.77	1,485,490.02	73,728,388.32	6,801,434.95	59,393,676.39
All	164,999,806.79	65,652,666.99	11,809,874.29	4,047,743.14	5,671,810.65	121,410,730.34	16,849,986.02	356,248,833.72

Figure 5. Landcover classification derived from Sentinel-2 remote sensing imagery at a 10m resolution, summarized for seven Migratory Bird Joint Ventures, which include the Northern Great Plains (NGPJV), Oaks and Prairies (OPJV), Prairie Habitat (PHJV), Playa Lakes (PLJV), Prairie Pothole (PPJV), Rainwater Basin (RBJV), and Rio Grande (RGJV). Light green indicated the amount of undisturbed grass classified within the potentially undisturbed lands layer (PUDL), whereas dark green indicates the total amount of disturbed and undisturbed grass (i.e., both inside and outside the PUDL layer) classified in each joint venture.

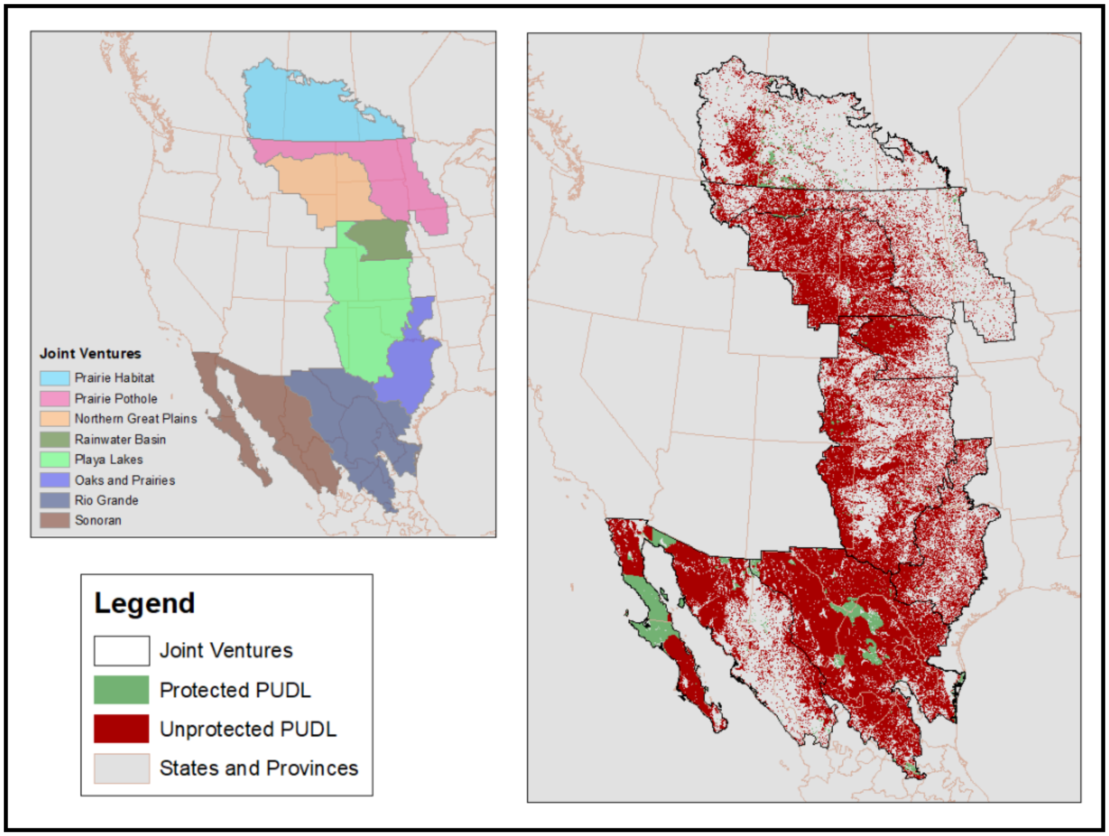


Loss vs. Protection

We estimated 7.23% of PUDL layer was protected (34.05 million acres; Figure 6, Table 2). Roughly 84% of the protected PUDL occurred in Mexico and Canada. The Mexico portion of the Sonoran and Rio Grande JV, and the Prairie Habitat JVs had 15.73, and 8.13, 4.82 million acres of protected PUDL, respectively (19.60% 7.71%, 19.08% of their respective PUDL layers were protected). Roughly 80% of the protected PUDL in the US occurred in the Prairie Pothole, Rio Grande (US portion), and Playa Lakes JVs, containing 2.09, 1.25, and 0.94 million acres, respectively (6.98%, 3.81%, and 1.19% of their respective PUDL layers were protected). Northern Great Plains, Rainwater Basin, and Oaks and Prairies JVs had the smallest amounts of protected PUDL, containing 0.56, 0.25, and 0.24 million acres, respectively (0.88%, 1.35%, and 0.72% of their respective PUDL layers were protected).

Figure 6. Protected and unprotected potentially undisturbed lands (PUDL) within eight Migratory Bird Joint Ventures of the Great Plains region. Figure A) depicts the spatial extent of protected and unprotected PUDL, and figure B) summarizes the amount of protected and unprotected PUDL cover and protected PUDL in each joint venture.

A)



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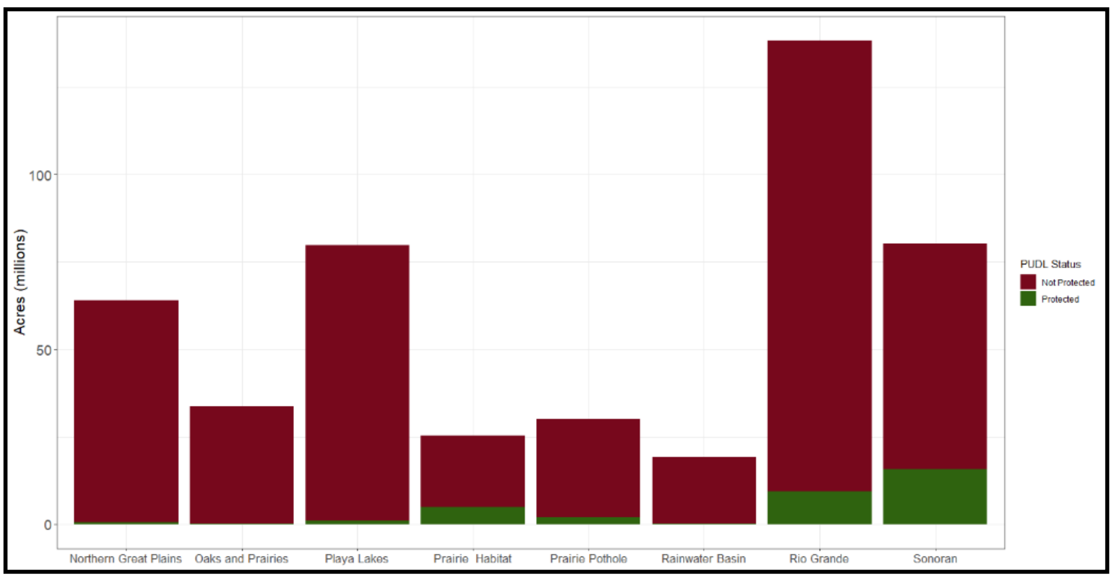


We presented a range of loss rate estimates for undisturbed grassland, shrubland, and wetland complexes per JV based on annual and periodic time-series landcover datasets (Figures 7 & 8, Table 5). Prairie Habitat and Prairie Pothole JVs had the highest undisturbed cover loss rate estimates based on annual time-series data (-2.62%/yr and -2.27%/yr, respectively) and periodic time-series data (-0.44%/yr and -0.65%/yr, respectively). Rainwater Basin and Playa Lakes JVs had high annual loss rate estimates from annual landcover data (-0.54%/yr and -0.61%/yr, respectively), but much lower estimates from periodic landcover data (-0.22%/yr and -0.19%/yr, respectively). Oaks and Prairies and Northern Great Plains JVs had lower loss rate estimates from both annual (-0.43%/yr to -0.30%/yr, respectively), and periodic landcover data (-0.13%/yr to -0.11%/yr, respectively). The US portion of the Rio Grande JV had the lowest loss rate estimate as calculated by either method (-0.07%/yr from CDL and -0.05%/yr from NLCD). In Mexico, loss rate estimates from INEGI for Sonoran and Rio Grande JVs were -0.03%/yr and -0.22%/yr, respectively.

Figure 7. Tracking change in total cover and undisturbed cover over time within Migratory Bird Joint Ventures using annual cropland data layers. Data include Agriculture Agri Foods Canada Annual Crop Inventory in Canada, and National Agricultural Survey Statistics Cropland Data Layer in the US. Cover is defined as grass, shrub and wetlands. Total cover tracks the amount of cover present each year despite past classifications. Undisturbed cover tracks the amount of cover each year that has never been classified as crop or developed. The three gray trend lines estimate the rate of change for total cover (i.e. dotted line), undistured cover (i.e. dot/dash line), and total and undisturbed cover together (i.e. solid line).

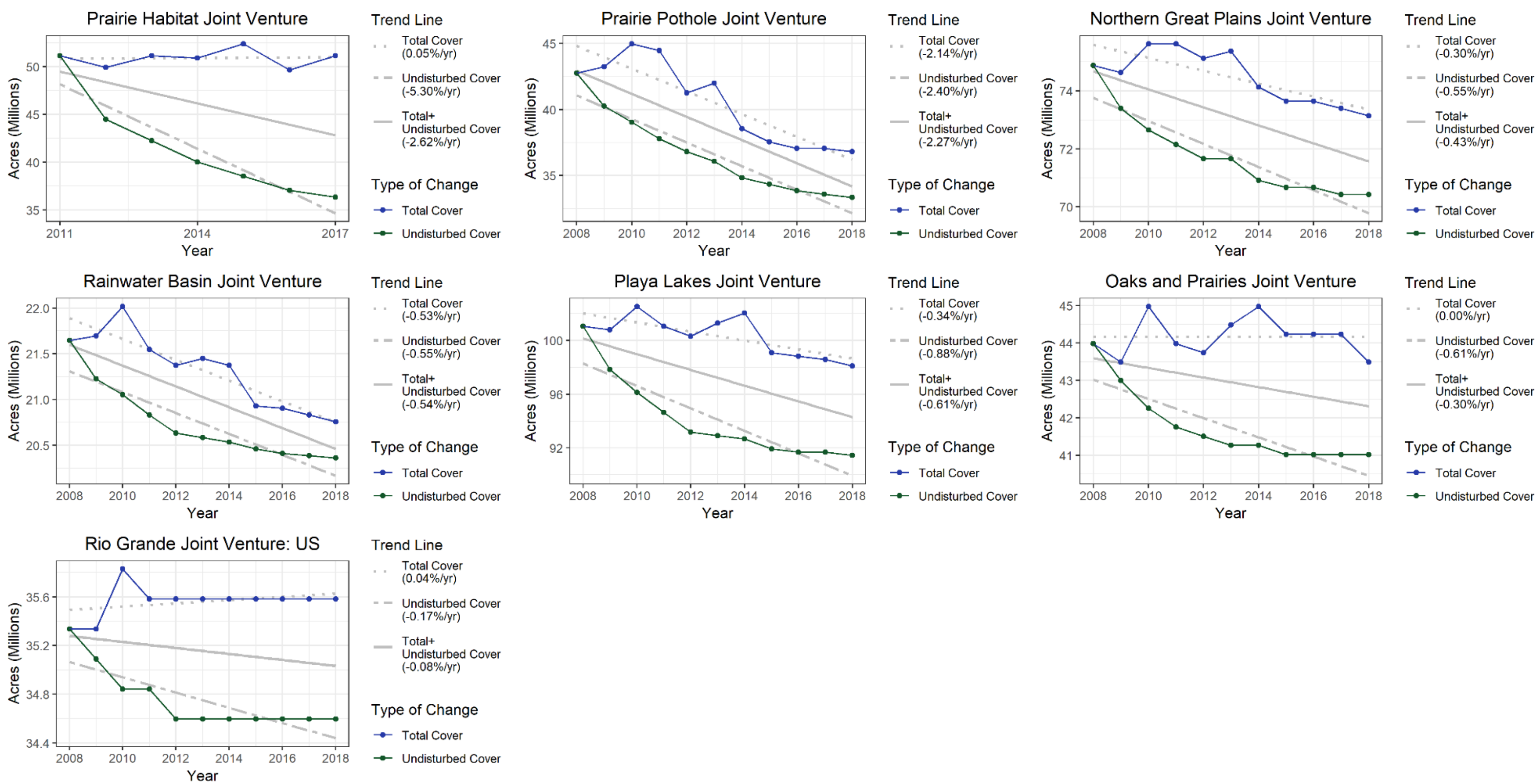


Figure 8. Tracking change in total cover and undisturbed cover over time within Migratory Bird Joint Ventures using periodic landcover data layers. Data include Agriculture Agri Foods Canada Land Use in Canada, National Land Cover Database in the US, and Instituto National de Estadistica y Geographia Uso de Suelo y Vegetation in Mexico. Cover is defined as grass, shrub and wetlands. Total cover tracks the amount of cover present each year despite past classifications. Undisturbed cover tracks the amount of cover each year that has never been classified as crop or developed. The three gray trend lines estimate the rate of change for total cover (i.e. dotted line), undistured cover (i.e. dot/dash line), and total and undisturbed cover together (i.e. solid line).

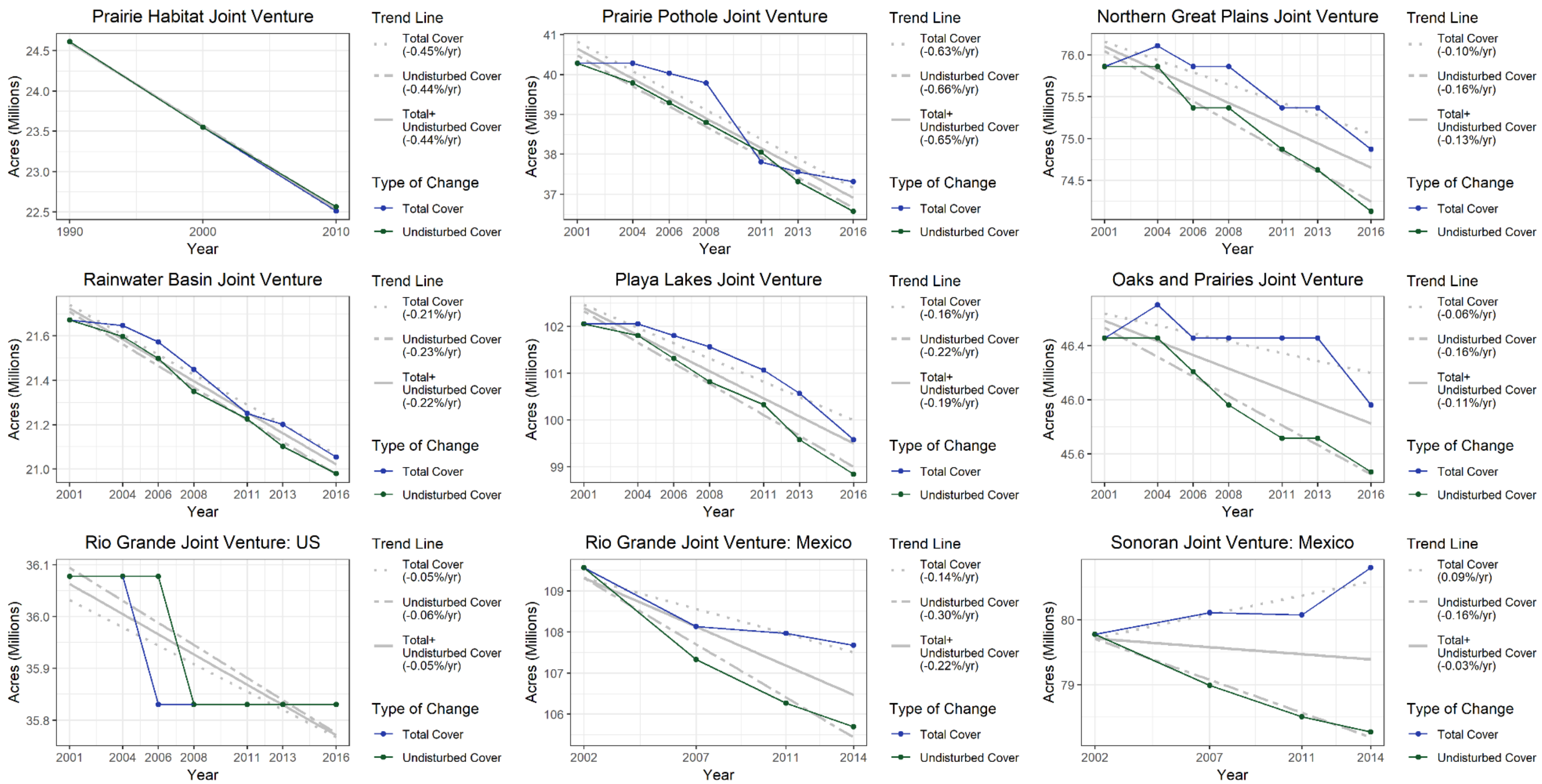


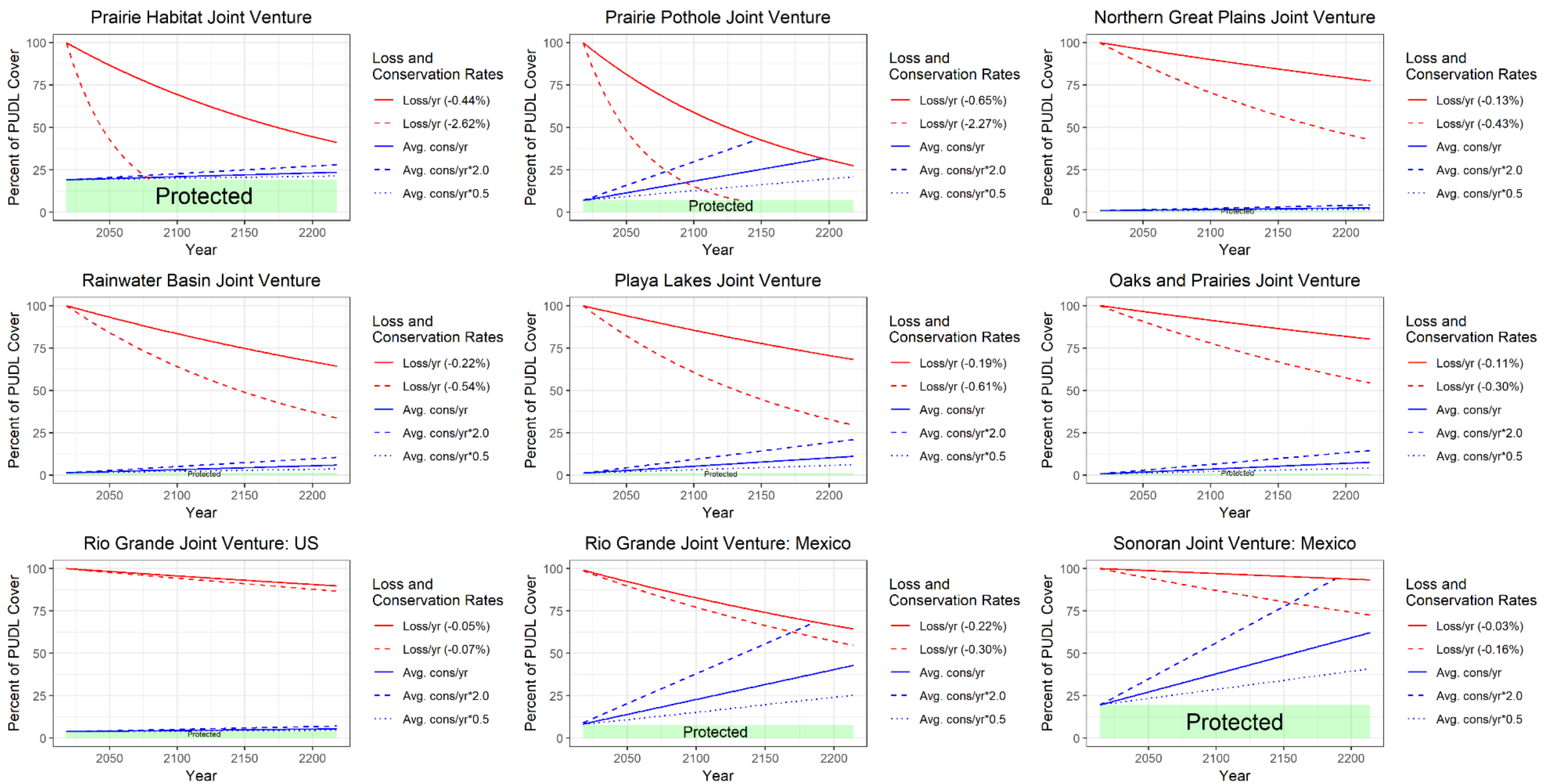
Table 5. Annual rates of grassland loss and average annual acres protected were calculated for eight Migratory Bird Joint Ventures over a 10+ year period. Average annual acers protected were estimated using a 10 year mean using protected lands layer databases. Loss estimates were derived from annual cropland and periodic landcover datasets. We calculated the rate of change for the total amount and the undisturbed amount of grass/shrub/wetlands present each year, where disturbance is classified as being identified as crop or developed. We also present rates of grassland change from other sample-based studies/literature.

	Protection: Protected Lands Data		Landcover Change: Annual Crop Classification Data				Landcover Change: Periodic Landcover Data			
Joint Venture	Years	Avg. Annual Ac Protected	Years	Rate Undisturbed (SE)	Rate All (SE)	Rate Total (SE)	Years	Rate Undisturbed (SE)	Rate All (SE)	Rate Total (SE)
Prairie Habitat	2007-2016	5,626.16	2011-2017	-5.30 (0.71)	-2.62 (1.76)	0.05 (0.36)	1990, 2000, 2010	-0.44 (0.004)	-0.44 (0.005)	-0.45 (0.003)
Prairie Pothole	2005-2014	41,780.41	2008-2018	-2.40 (0.20)	-2.27 (0.41)	-2.14 (0.34)	2001, 2004, 2008, 2011, 2013, 2016	-0.66 (0.03)	-0.65 (0.06)	-0.63 (0.11)
Northern Great Plains	2005-2014	5,358.55	2008-2018	-0.55 (0.07)	-0.43 (0.14)	-0.30 (0.07)	2001, 2004, 2008, 2011, 2013, 2016	-0.16 (0.02)	-0.13 (0.02)	-0.10 (0.02)
Rainwater Basin	2005-2014	4,389.60	2008-2018	-0.55 (0.08)	-0.54 (0.11)	-0.53 (0.08)	2001, 2004, 2008, 2011, 2013, 2016	-0.23 (0.01)	-0.22 (0.01)	-0.21 (0.02)
Playa Lakes	2005-2014	39,479.39	2008-2018	-0.88 (0.10)	-0.61 (0.25)	-0.34 (0.14)	2001, 2004, 2008, 2011, 2013, 2016	-0.22 (0.02)	-0.19 (0.02)	-0.16 (0.02)
Oaks and Prairies	2005-2014	11,615.15	2008-2018	-0.61 (0.11)	-0.30 (0.22)	0.0002 (0.12)	2001, 2004, 2008, 2011, 2013, 2016	-0.16 (0.02)	-0.11 (0.03)	-0.06 (0.03)
Rio Grande (US)	2005-2014	2,697.61	2008-2018	-0.18 (0.04)	-0.07 (0.09)	0.04 (0.04)	2001, 2004, 2008, 2011, 2013, 2016	-0.06 (0.02)	-0.05 (0.01)	-0.05 (0.02)
Rio Grande (MEX)	2008-2017	186,067.51					2002, 2007, 2011, 2014	-0.3 (0.04)	-0.22 (0.06)	-0.14 (0.04)
Sonoran	2008-2017	171,184.52					2002, 2007, 2011, 2014	-0.16 (0.01)	-0.03 (0.09)	0.09 (0.04)

The Mexico portion of the Rio Grande and Sonoran JVs had the highest rate of protection, with a 10-year average annual conservation effort of 186,067 and 171,185 acres, respectively (Figure 9, Table 5). In the US, the Prairie Pothole, Playa Lakes, and Oaks and Prairies JVs had the highest 10-year average annual conservation rates of 41,780, 39,479, and 11,615 acres, respectively. The remaining regions' 10-year average annual conservation efforts ranged from 2,698 acres in the US portion of the Rio Grande JV to 5,626 acres in the Prairie Habitat JV.

Projection of undisturbed grassland loss versus protection over the next 200 years showed spatially variable results across the joint ventures (Figure 9). Despite the variability of loss and protection rate estimates between the JVs, in general, undisturbed grassland loss well exceeded rates of protection in each JV. Average annual estimates of PUDL loss in the next 10 years using low and high loss rate estimates was 19.37 - 103.61 times higher, respectively, than the average annual protection estimate in the Prairie Habitat JV (i.e. average acres lost:average acres protected). It was 15.46 – 50.37 times higher in the Northern Great Plains JV; 9.54 – 23.04 times higher in the Rainwater Basin JV; 4.51 – 14.55 times higher in the Prairie Pothole JV; 3.80 – 11.95 in the Playa Lakes JV; 3.17 – 8.58 times higher in the Oaks and Prairie JV; 6.09 – 8.51 in the Rio Grande (US) JV; 1.62 – 2.20 times higher in the Rio Grande JV (MEX); and 0.14-0.74 times higher Sonoran JV (MEX).

Figure 9. Rates of loss versus protection for potentially undisturbed lands (PUDL) projected into the future 200 years for 8 Migratory Bird Joint Ventures in the Great Plains regions; The Rio Grande Joint Venture has separate graphs for the US and Mexico regions, and the Sonoran Joint Venture only includes estimates for its region in Mexico. Two loss rate estimates were derived from landcover data, and the amount of protected PUDL (green) and three rates of protection (average, and averaged halved and doubled) were derived from protected lands layers available in each country.



Discussion

<u>PUDL Layer</u>

A tri-national grassland assessment of undisturbed lands is an important planning tool given the full annual-cycle geographies of migratory birds in the Great Plains. Having a common source for landscape scale conservation planning will allow all JVs to implement conservation strategies within their respective JVs that build into full annual-cycle conservation for priority species across JVs. However, conservation planning initiatives need to consider the differences in the datasets used to create the PUDL layer and how it affects estimates in each country.

The Common Land Unit dataset (CLU) used in the US is an excellent resource for capturing disturbance (Table A1). Its fine-scale delineations of field boundaries are superior to that of a 30m pixel resolution, and there are no uncertainties in classification. However, not all prior disturbances can be captured through this dataset. For example, some cropland parcels may not be included in the CLU dataset because they were not enrolled in a USDA program. Therefore it is more likely that the PUDL layer will include false positives than false negatives in the United States. In contrast, the Agriculture and Agri Foods Canada Land Use and Annual Crop Inventory datasets used to produce the PUDL layer in Canada are prone to misclassification at the pixel level, and our methods accumulate those errors over the years. This means that in Canada the PUDL layer is likely to have more false negatives than in the US or Mexico. In Mexico the INEGI dataset is produced at irregular intervals and at a relatively large scale (1:250,000), therefore more recent disturbances or disturbances occurring during interim periods may not have been captured. Therefore, this region's PUDL layer will have more false positives than negatives. It should be noted however, that despite the large scale of the dataset, the amount of arable land in the Rio Grande Joint Venture is limited and cropland is less spread out and more localized, making detection and mapping easier. It should also be noted that the supervised classification of landcover within the PUDL layer should help capture false positives (i.e. cropland) within the layer, and the identification of the undisturbed grass cover class outside the PUDL layer could help identify areas that were removed due to misclassification of crop in the landcover layers used to develop the PUDL layer (i.e. false negatives).

Supervised Classification

Supervised classification efforts performed better in the northern and eastern regions than for the western and southern regions. Overall accuracy, and grass/shrub accuracy was often below a target accuracy of 80%. Even with a three year collection of imagery, cloud contamination was an issue and often capturing the period of greenup was missed. A finer spatial resolution did help identify small features (e.g., forested ravines), however accurately capturing the heterogeneity of the landscape at a finer resolution also required increased training data and analysis effort. Even the ground-truthed dataset in the Rainwater Basin JV required extra training data for grasslands that were under sampled in the west.

While the landcover product we produced has sub-optimal accuracy in some regions, we feel that we've established methods and training data that can be easily shared, augmented, and implemented in Google Earth Engine for future improvement (see Appendix B for google earth engine code with training data). Some recommendations to improve classification accuracy would be to use the newly uploaded bottom-of-the-atmosphere Sentinel-2 level-2A product, which has a start date of March 2017. In addition the exploration of other remote sensing indices, or soils and landform datasets could help improve classification accuracy. Fisher et al. (2018) has recently evaluated the use of high-resolution Light Detection and Ranging (LiDAR) for classification of native grasslands. They demonstrated high confidence in the ability to identify tractor furrows in fields that have been plowed but have since revegetated with native and tame grasses. These techniques are currently being used by the South Dakota State University Extension Service to identify undisturbed grasslands throughout the state with high accuracy. However, LIDAR data is currently unavailable in much of the Great Plains and Chihuahuan Desert.

Loss vs Protection

Projecting loss and protection rates into the future across the study area is a good visual exercise for estimating which regions need the largest conservation effort, and which regions are not at risk or are doing well at stemming grassland loss (Figure 7). However, there are many assumptions that must be recognized to better understand what is being presented. We are assuming that the undisturbed habitat loss rates derived from grass/shrub/wetland complexes in the start year of our time-series dataset, will also apply to the current PUDL layer, which is likely an overestimate as a large portion of PUDL occur in areas that are less prone to cultivation (WWF 2018). Visualization of undisturbed grassland over time supports this concept, as the rate of change tends to decrease later in the time-series. In addition, some JVs such as Rio Grande have less arable land (e.g. Chihuahuan Desert, Sierra Madres) but are losing grassland quickly in valley regions, so summarizing loss at a JV scale may not accurately represent the extent of the problem. We are also assuming that the entirety of the conservation effort each year will be put towards protecting PUDL, which is unlikely, however these estimates represent what is possible given the average effort. Many JVs employ a variety of conservation programs to ensure grasslands remain on the landscape, including fee-title acquisition, conservation easements, cost-share, or other short-term programs. Keeping the remaining undisturbed grasslands part of working agricultural operations is a key conservation strategy in certain regions. Often cost-share for grazing infrastructure and conservation easements can be combined to achieve this objective.

We recognize that estimating undisturbed grassland loss rates via landcover classification products from remote sensing data lacks accuracy due to the uncertainty associated with classifying different cover types, the sensitivity/specificity of the models used to classify certain cover types, and the type of classification used (pixel-based or object-based). However, comparing loss rates across JV boundaries is an important conservation planning exercise. While the loss rates we presented are crude estimates, we did employ methods that lessen in the influence of model uncertainty in classification, balance the differences inherent in classification models (annual crop-based vs. periodic landcover-based), and supply estimates from datasets that are relatively comparable across national boundaries.

We also recognize that protection estimates are subject to data limitations which hinder accuracy. This is largely due to the lack of complete protection data or how protection is defined across boundaries. Presentation and review of the best currently available data is a starting point and may urge the improvement of these data sources. Protection estimates presented here are limited to those lands that meet IUCN definition for protection, and these lands are often only a subset of each protected lands spatial layer. There are other protected lands that may not have a clear definition, or have a definition of protection that allows disturbance such as mineral extraction, which would prohibit their inclusion under IUCN standards (i.e. State Land Board lands; GAP status code 2 or 3). In some regions these other protected lands can make up a large percentage of the PUDL layer; for example, 20.49% of the Norther Great Plains PUDL layer is composed of other protected lands such as Bureau of Land Management (BLM) but only 0.88%

is protected as defined by IUCN. In all of the U.S. JVs in the Great Plains, BLM lands within the PUDL layer total 8.1 million acres (Norther Great Plains JV 4.91, Prairie Pothole JV 2.55, and Playa Lakes JV 0.63). The Prairie Pothole JV considers BLM land as part of the conservation estate, although these lands do not have the extent of oil and gas exploration compared to other areas like the Powder River Basin in Wyoming. Very few JVs have developed conservation estate data that provide a comprehensive ranking of protection levels across the range of landownership. Maintaining these data will enable JVs to track and understand the level of protection in their respective geographies and can be aggregated for a more accurate overall conservation estate layer.

While our trend analyses are focused on potentially undisturbed grassland, it is important to note that when tracking total grass/shrub/wetland cover the trends were often less severe, stable (e.g. Oaks and Prairies), or increasing (e.g., Prairie Habitat Joint Venture). Restoring grassland is an important conservation tool (e.g., CRP), however when coupled with a strong decline in potentially undisturbed grass (e.g. native grass), the underlying processes should be given greater scrutiny. For example, these kinds of trends have spurred new policy such as the Sob Buster program in the United States, which was established to prevent producers from putting cropland into a conservation program and then breaking native sod to replace the cropland that was taken out of production. Furthermore, restoration efforts need to recognize the system in which they are being placed, and seed with ecologically relevant vegetation and provide the ecological drivers organisms evolved with.

Conservation Planning

Our analyses estimated the spatial distribution of undisturbed land, the landcover composition within the PUDL layer, and a spatial summary of grassland loss versus protection. These three tools can help support conservation decisions across the region. While each JV faces unique challenges, these tools serve as a baseline for tracking future change and support decisions for moving forward. In general, these tools can support common conservation decisions regarding land protection, enhancement, or restoration.

Canada for example has adopted the Conservation on Biological Diversity Strategic Plan and has agreed to protect 17% of their land and freshwater by 2020 (Coristine et al. 2018). They have ~6% more to protect to reach that goal based on current protected lands layers. The Prairie Habitat JV contains a high richness of species at risk, a high undisturbed grassland loss rate, a low protection rate, and a low proportion of this region is protected PUDL (~3%). Indeed, timeline projections illustrate a need for increased protection effort in the PHJV, and the PUDL layer could serve as a useful tool to direct protection to help Canada reach their legal responsibility of protecting 17% of their land and stem the decline of biodiversity in this region.

Conservation prioritization and targeting can be enhanced when utilizing the PUDL layer in concert with or integrating it into other spatial tools. It would be useful to use the PUDL layer in conjunction with a risk-of-conversion layer (Olimb and Robinson 2019) or resiliency layer (Grand et al. 2019) to prioritize protection of PUDL based on conservation goals. Similarly, the supervised landcover classification layer and the PUDL layer could be used as covariates in species distribution models, which would also be beneficial for directing full-annual cycle conservation efforts for priority species. This would be especially useful for species that span political boundaries and modeling efforts that benefit from a greater thematic resolution of grassland conditions. In addition, the supervised classification layer and the PUDL layer could be used to target areas with shrub encroachment for enhancement efforts, or target cropland near or between large blocks of grassland for restoration efforts to increase patch size and/or grassland connectivity.

These are just a few examples of how these tools can support conservation work in the Great Plains. Making these tools publically available will support other partners' projects and further conservation work in the region. We hope that these tools can be expanded, improved, and updated as we work to stem grassland decline and loss of biodiversity in the Great Plains. This assessment is only the first step in a process to galvanize the eight JVs to move forward as a network for grassland conservation. Joint ventures are built on the power of partnerships and we must bring people and resources together to address the complex issues facing our grasslands.

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Appendix A: Detailed Methods

Methods

PUDL: Country Specific Data Sources and Methods

Data Sources and Methods: United States

In the United States we employed a deductive approach using a proprietary geospatial time-series vector dataset and other sources to create a PUDL layer. The time-series dataset was developed by United States Department of Agriculture (USDA) Farm Service Agency (FSA) and is called the Common Land Unit (CLU) dataset (FSA 2014). A common land unit is defined as the smallest unit of land that has a boundary, and a common land use, owner, and producer association. CLU was first established in 1998 and in some regions has incorporated spatial data dating back to 1956 via the Soil Bank program (i.e., paper maps). The FSA continually updates the CLU dataset by spatially delineating land units that have participated in USDA programs. Therefore any lands that are cultivated but not enrolled in USDA programs will not be added to the dataset. Additionally, any data pertaining to cultivation prior to 1956 are not available. Furthermore, as detailed by Bauman et al. (2016), if a parcel has been historically cropped but has a change in ownership or use that prohibits cultivation in perpetuity, then those areas can be converted to a “non-crop” indicator code or removed from the CLU dataset; those grassland areas are henceforth referred to as “go-back lands”.

We received ten years of CLU data from FSA under a memorandum of understanding. Most counties in the US portion of our study region had ten years of CLU data except for some counties in New Mexico that were lacking data in 2008. CLU coverage at the county-level was variable both spatially and temporally. Generally, CLU coverage was lower around the perimeter of our study area and in some southern counties. In some counties, CLU spatial coverage would change over the ten year period suggesting the presence of go-back lands.

CLU spatial delineation is currently accomplished using heads-up-digitization of orthophotography in a Geographic Information System (GIS), but has utilized paper aerial photography and maps in the past. The dataset has a dedicated team of data stewards at national, state, and local levels, which utilize digitizing centers, and a standardized protocol and suite of GIS tools for digitization and quality control purposes. CLU parcels are associated with a table of attributes; a landcover attribute field indicated landcover classification and a field called 3_CM was added in 2012, which indicates if a parcel has ever had a cropping history despite its current cover.

There are ten landcover types identified in the CLU dataset: rangeland, cropland, other agriculture, urban, water body, forest, barren, mined land, permanent ice and snow, and tundra. Cropland is defined as "…newly broken…currently being tilled…not currently tilled but have been tilled in a prior year…" and other similar scenarios (FSA 2014). The classification other agriculture is a catch-all for areas on agricultural land not used for production, which include "…farmsteads, holding areas for livestock such as corrals, breeding and training facilities on horse farms, farm lanes and roads, ditches and canals, small farm ponds, and similar uses". We did not incorporate the other agriculture landcover class into our analyses because under exploratory analyses we determined that often large drainages were included in this class, and given their topographic relief these areas are often undisturbed. To identify lands that have a cropping history, and increase our chances of removing go-back-lands, we used multiple years of CLU data from 2008-2011 and 2013-2018, and both the landcover and 3-CM fields. Each year we extracted any parcel that was identified as cropland or had a cropping history and erased these areas from a polygon that delineated our study area in the U.S.

We used the 2011 National Land Cover Database (NLCD; Homer et al. 2011) to remove bare ground, forested, and developed areas. We extracted pixels identified as bare ground, forests, and developed areas, converted those pixels to polygons, and erased them from our study area. The NLCD is created by a partnership of federal agencies called the Multi-Resolution Land Characteristics Consortium. It is a 30 m resolution raster depicting broad landcover types that were classified using decision tree methods and 2011 Landsat imagery. The landcover types removed are defined as bare ground where vegetation makes up less than 15% of total cover, trees greater than 5 m tall that make up greater than 20% of total vegetation cover, and developed areas that range from urban lawns to areas where impervious surfaces make up 80-100% of the total cover.

We used the USGS high resolution National Hydrologic Database (NHD; McKay et al. 2012) to extract any waterbody >= 40 ac and erased these features from the U.S. portion of our study region. We did not however remove playa lakes >= 40 ac. NHD is a vector dataset that contains waterbodies mapped at a 1:24,000 scale or better. The dataset is updated and maintained through partnerships with state and collaborative bodies. A 40 ac threshold was selected to maintain methods utilized by similar past studies (Bauman et al. 2016) that removed large waterbodies to obtain a more accurate assessment of undisturbed grass/shrub/wetland complexes.

Lastly, we erased areas identified as roads and rails using the TIGER/Line transporation dataset which includes geospatial extracts from the U.S. Census Bureau's Master Address File/Topologically Integrated Geographic Encoding and Referencing database (MAF/TIGER; TIGER/Line 2017). TIGER/Line shapefiles contain nationwide street centerline geospatial data in vector format. It was first released in 1989 and derived from United States Geologic Survey (USGS) Digital Line Graph (1:1,000,000-scale) and has been continually updated since then using data provided by partners from local, state, and federal governments. We removed paths and trails from the dataset, buffered major roads by 25 m and local roads and rails by 15 m, and erased these areas from our study area. These areas were removed because they represent areas of disturbance. The buffer distances we selected were informed using a sample of measurements across road types where the straight line distance includes the road surface and ditches (i.e., generally fence line to fence line). See Appendix A for classification codes used in analysis.

Data Sources and Methods: Canada

In the Prairie Habitat Joint Venture we employed a deductive approach using publically available raster time-series landcover data and other data sources to create a PUDL layer. We used 30 m landcover time-series rasters from Agriculture Agri-Foods Canada (AAFC). We used nominal years 1990, 2000, and 2010 Land Use datasets (LU; http://www.agr.gc.ca/atlas/supportdocument_documentdesupport/aafcLand_Use/en/ISO_19131_Land_Use_1990__2000_2010_Data_Product_Specifications.pdf) and 2011-2017 Annual Crop Inventory (ACI; http://www.agr.gc.ca/atlas/supportdocument_documentdesupport/annualCropInventory/en/ISO%2019131_AAFC_Annual_Crop_Inventory_Data_Product_Specifications.pdf) datasets to identify cumulative cropland and masked these areas from the 2017 ACI. We then identified and masked barren, forest, and developed landcover types from the 2017 ACI and converted the raster to polygon.

AAFC LU datasets were created using multiple data sources and a “preponderance of evidence” set of rules. It was created for all of Canada south of 60^0 N and has overall accuracy assessment of 89.1%, 90.6%, and 94.7% for 1990, 2000, and 2010, respectively (if water and wetland classes are grouped together). AAFC ACI datasets were created using remote sensing data, training and testing data, and decision tree based classification methods. Radar data came from RADARSAT-2 (2011-2017), and optical data came from Landsat 5 (2011-2012), Landsat 8

(2013-2017), Sentinel-2 (2016-2017), and Gaofen-1 (2016-2017). These methods have produced overall accuracy for 2011-2017 cropland classes >= 85%.

We used the World Wildlife Fund hydroLAKES database to identify and erase large water bodies (>= 40 ac) from the study area (Messaner et al. 2018). This is a global database that maps open water >= 10 ha as polygons. Sources to create this database vary by location. In Canada the dataset is produced from Canadian hydrographic dataset (CanVec; 1:50,000 scale, Natural Resources Canada 2013), Shuttle Radar Topographic Mission Water Body Data (1 arc-second raster, Slater et al. 2006), Global Lakes and Wetlands Database (1:1 million scale or better, Lehner and Doll 2004), Global Reservoir and Dam database (1:1 million scale or better, Lehner et al. 2011), and World Wildlife Fund mapping 1:1 million scale or better).

Lastly we used the National Road and Rail Network vector dataset to erase roads and rails throughout the study area (http://ftp.maps.canada.ca/pub/nrcan_rncan/vector/geobase_nrwn_rfn/doc/GeoBase_nrwn_en_Catalogue.pdf). Prior to erasing these areas we buffered major roads by 25 m, and minor roads and rails by 15 m. The National Road and Rail Network databases are produced through intergovernmental partnerships that provide data updates at least once a year using a homogenous and standardized approach to represent centerline road phenomena at an approximate resolution of 1:10,000. See Appendix A for classification codes used in analysis.

Data Sources and Methods: Mexico

In the Mexico portion of the Rio Grande Joint Venture we employed a deductive approach using publically available vector time-series landcover data and other data sources to create a PUDL layer. We used INEGI uso de suelo y vegetation time-series landcover datasets, serie 3-6 (INEGI 2005, 2009, 2013, and 2016). These are vector data produced from remote sensing imagery at a 1:250,000 scale. Serie 3-6 were produced using Landsat imagery from the following sensors and years: serie 3 used Landsat 7 ETM+ imagery from 2002, serie 4 used Landsat 5 imagery from 2007, serie 5 used Landsat 5 imagery from 2011, and serie 6 used Landsat 8 imagery from 2014. For each serie we used landcover classifications to extract areas defined as croplands and erased these areas from the most recent landcover layer serie 6. We then identified and remove barren, forest, and developed landcover types from serie 6.

We used WWF hydroLAKES dataset to identify and erase water bodies >= 40 ac from our study area. Lastly, we used OpenStreetMap transportation dataset to identify roads and rails and erased these areas from our study area (www.openstreetmap.org). Tracks and trails were removed from the dataset, and major roads were buffered by 25 m and minor roads and rails were buffered by 15 m before erasing these regions from our study area. OpenStreetMap is an open source dataset built by a community of amateur to professional mappers using GPS, aerial imagery, or maps to add geospatial data to the OpenStreetMap database. Geofabrik processes these data using consistent and standardized methods, updates the datasets daily, and makes the data available for download as a shapefile (Ramm 2019; https://download.geofabrik.de/north-america/mexico.html). See Appendix A for classification codes used in analysis.

Supervised Classification

Training Data

Five indices were created from a 2016-2018 Sentinel-2 image collection within our study area. We processed each image in the collection by masking cloud cover using the cloud mask band. We then calculated a Normalized Difference Vegetation Index band (NDVI), a Red Edge Index (REI), and a day of year band that reflected the ordinal date the image was created. NDVI and REI both measure greenness however the REI is less prone to saturation in areas that have high density biomass (Clevers 1994). We then created a median composite and a greenest pixel composite of the image collection. The median composite calculated the median value for each band per pixel. In the Prairie Habitat JV we truncated the three year dataset from April 1st to September 30th for each year to limit the effect of a prolonged winter on median image composites; we used the full three year dataset for the remaining JVs' median composites and for all JVs' greenest pixel composites. The greenest pixel composite used a per pixel ordering function based on the NDVI band, where the pixel with the highest NDVI value was selected along with its associated band values from that point in time. We derived peak NDVI and the ordinal date and REI associated with peak NDVI from the greenest pixel composite. We calculated the difference between median NDVI and peak NDVI as a measure of how green a pixel became. Lastly, we performed a Tasseled-Cap linear transform of the median composite bands that represented greenness, wetness, and brightness of the image (Kauth and Thomas 1979).

We created our own landcover class reference points to sample covariate data to use as training data for the model. Reference points were created by interpreting orthoimagery available through Google Earth Engine (DigitalGlobe, Google 2018). Reference points were labeled with the landcover class that made up the majority of a 10 m x 10 m area around the point with cover typically greater than ~50% of the area. Interpretation and placement was guided by the following geospatial data: the PUDL layer, 2017 AAFC ACI in Canada, 2011 NLCD in the US, INEGI serie 6 in Mexico, USDA Conservation Reserve Program data in the US (CRP; proprietary dataset), the Missouri Resource Assessment Partnership (MORAP) ecological systems classification datasets for Texas and Oklahoma (Elliott et al. 2014), false-color composites of median and greenest pixel composites, and google street view when applicable. We considered areas disturbed grass if they were outside the PUDL layer and appeared to be grass. We considered areas potentially undisturbed grass if they were within the PUDL layer and appeared to be grass. We believed that there would be spectral differences between these two grass classifications based on common restoration and management practices, wherein restored grasslands are often seeded with similar low species diversity mixes containing non-natives and are generally left idle (CRP) or used for hay production or small grazing pastures. We considered an area open water if water were visible in both the median and greenest pixel composites, representing more permanent water bodies. We considered an area bare ground if it appeared completely devoid of vegetation. These regions were generally located in areas of bare rock, soil, or urban landcover/structures. We considered an area cropland if it appeared plowed and seeded. We considered an area forest if it contained tall trees, generally large textured and often casting a shadow, and an area shrub if it appeared small-rounded, textured, and often casting a minimal shadow.

Models were constrained to areas that generally represented large ecoregions within each JV (CEC Level III ecoregions). Our methods were based in the assumption that phenology of green-up between native and non-native grasses would enable the identification of potentially disturbed vs. undisturbed lands (Olimb et al. 2017); however, these differences would be most meaningful in regions with similar soils and climates. Depending on how much the granule overlapped the model region, we selected 10-20 reference points per class in every other granule that covered the region. If we could not establish reference points for all classes in each sample granule we added points to other sample granules. An effort was made to space points out over a granule if possible. After the model was trained and applied with the balanced dataset we added more training data in areas of obvious misclassification. In total we used 33,331 reference points, and 4,227 of those were points added in areas of misclassification (Table 4).

Training data for the Rainwater Basin JV was established differently because they were able to supply reference points that were collected on the ground in 2017 and 2018 as part of an ongoing ecological systems mapping study (A. Bishop pers comm.). Reference points consisted of road-based samples that labeled the predominant landcover, the percent cover, and the top three species that composed the cover. We coded these species as native or non-native and each reference point was scored a value of 0-3 based on the number of dominant native species. We also coded each point that was collected within the PUDL layer. For potentially undisturbed grassland reference points we only selected points from 2018 (due to data collection disparities between the years for grassland landcover), that were collected within the PUDL layer, had a landcover layer of grassland or marsh, a native score of 3, and an herbaceous percentage of 76-100. Disturbed grass reference points were selected using 2018 and some of 2017 data. For 2018 data we selected points that were labeled grassland, marsh, grass farm, or CRP, that were outside the PUDL layer, had a native score of 0-1, and had an herbaceous percentage of 76-100. In 2017 we selected similar points except we excluded grassland and marsh landcovers. We selected all urban and bare, and water landcover data for the developed/bare, and water reference points. We selected all crop, shrub, and forest landcover data as reference points if they had an herbaceous/shrub/tree percentage of 76-100. Reference points were visually inspected to ensure they aligned with our interpretation of aerial imagery. Crop, forest, and undisturbed grass had just over 400 data points each and were thinned to 400 through random selection. Water, developed/bare, shrub, and disturbed grass data points were considerably less (n=84, 30, 67, and

284, respectively) and reference points were added using aerial interpretation methods to reach 400 points for each class.

Model Tuning and Validation

After extracting covariate data at reference point locations we exported the data table and tuned the model using the randomForest package in R (R Core Team 2018, Liaw and Wiener 2002). We tested the optimal number of variables per split and number of trees that would balance computation time and accuracy. We let the variables per split range from 2-4, and the number trees range from 101-501 trees increasing by 100. For each combination we ran 100 models and calculated the mean out-of-bag error. We selected the number of variables per split that produced lower error estimates over the range of trees, and we selected the number of trees when a 100 increase in the number of trees stopped improving the error rate by >=0.15%. Generally two variables per split and 301 trees were selected. We then set a seed that produced a similar out-of-bag error and reported the associated error matrix. Lastly, we trained the model in Google Earth Engine with the selected tuning variables, applied the model to the covariate images, and exported the landcover classification images for further processing in ArcGIS (i.e., clipping and mosaicking).

Loss vs. Protection Estimates

Loss rate estimates were calculated using different time-series datasets for each JV (Table A1). In Canada we derived landcover change estimates using 2011-2017 Agriculture Agri Foods Canada (AAFC) Annual Cropland Inventory (ACI). In the U.S. we used the 2008-2018 United States Department of Agriculture (USDA), National Agricultural Statistics Service (NASS) Cropland Data Layer (CDL; USDA NASS 2018). We also derived estimates using the periodic landcover datasets, including AAFC Land Use (LU; 1990, 2000, and 2010) in Canada, Multi-resolution Land Characteristics (MRLC) Consortium National Land Cover Database (NLCD; 2001, 2004, 2008, 2011, 2013, and 2016) in the U.S., and Instituto Nacional de Estadística y Geografía Uso del Suelo y Vegetación (INEGI; 2002, 2007, 2011, and 2014) in Mexico.

We obtained loss rate estimates from times series landcover data by tracking total cover and undisturbed cover each year (Figures 7 & 8). Total cover represented the total amount of grass, shrub, and wetland cover present in each year regardless of its disturbance history. Undisturbed cover represented the amount of undisturbed grass, shrub, and wetland cover present each year (i.e., tracking the amount of undisturbed cover over time). To do this we first calculated the total amount of grass, shrub, and wetland cover in the start year, and then recalculated the amount of cover remaining after masking/erasing any pixels/polygons that were classified as crop or developed each following year. Note that if an undisturbed pixel was reclassified as bare, water, or forest it would not be removed.

Prior to making any calculations or masking any layers in the U.S. or Canada we used a 5x5 pixel moving window on the 30m resolution landcover layers to remove any small isolated classifications of crop or grass (Wright and Wimberly 2013). These areas often have a 'salt-and-pepper' appearance and are caused by misclassification and model uncertainly. Smoothing the images helped reduce the noise in estimating rates of loss due to misclassification of crop or grass.

We then used log linear regression to obtain the annual rates of change for total cover, undisturbed cover, and all data points (i.e., a rate that lies between the change in total cover and undisturbed cover) within each JV. We did this because total change is an underestimate of loss that does not track those parcels that were cropped and then restored to grass, and undisturbed change is an over-estimate of loss because areas of crop misclassification within potentially undisturbed grass/shrub/wetland regions are accumulated over time; therefore, a rate of change between total cover and undisturbed cover is a more reasonable estimate.

Habitat conservation takes many forms, but long-term protection is not only arguably the best long-term investment, it can also be quantified across large landscapes using existing spatial datasets. Protection rate estimates were calculated using different vector datasets for each country that catalogued protected area boundaries and their attributes (Table A1). In the US we used the Protected Area Database of the United States (PADUS; USGS GAP 2018), in Canada we used the Conservation Area Reporting and Tracking System (CARTS; Vanderkam 2017), and in Mexico we used the World Database of Protected Areas (WDPA; UNEP-WCMC and IUCN 2018). These datasets include both fee-title and long-term easement data. Note that these are not comprehensive databases. For example, In the U.S. the PADUS dataset is estimated to include 95% of federal lands, and 60% of state, regional, local, and other preserved lands. Each dataset contains the type of protected area and the year of establishment. We only considered an area protected if it was attributed an IUCN category 1-6 (this aligns with GAP status codes 1 and 2 in the PADUS dataset). Only using IUCN category lands removed roughly half of the lands included in the PADUS and WDPA datasets; these lands were protected but prone to some development. For example, in the US the, State Board Lands represent a large majority of protected areas, but these lands are also open to cropping and mineral extraction so they were not included.

We calculated the percentage of PUDL protected and a recent 10-year average annual rate of protection for each JV. We calculated the percentage of the PUDL layer already in a protected status by clipping the protected lands layers with the PUDL layer for each JV. We calculated rates of protection using data from 2005-2014 in the US, from 2006-2015 in Canada, and from 2008-2017 in Mexico. Note that protection was temporally and spatially variable. For example in Canada we estimated a recent annual average protection effort of ~6,000 acres per year, however a 10-year average annual protection rate from 1996-2005 was calculated as ~74,000 acres per year. Lastly, we used these data to construct figures that depict the change in the PUDL layer projected into the future given estimated rates of loss and protection. See Appendix B for a list of landcover codes used to process the landcover data to derive loss rates estimates, as well as google earth engine code.

Table A1. Datasets used for analysis showing the dataset, acronyms, producer(s), year(s), use, description, and reference.

Dataset - Producer - Dates	Use	Description	Reference
Common Land Unit (CLU) -- United States Department of Agriculture (USDA), Farm Service Agency (FSA) -- 2008-2011 & 2013-2018	Used to identify disturbed lands in the US for the PUDL layer	A time-series vector dataset where a common land unit is defined as the smallest unit of land that has a boundary, and a common land use, owner, and producer association. CLU was first established in 1998 and in some regions has incorporated spatial data dating back to 1956 via the Soil Bank program (i.e., paper maps). The FSA continually updates the CLU dataset by spatially delineating land units that have participated in USDA programs. CLU spatial delineation is accomplished using heads-up-digitization of orthophotography in a Geographic Information System (GIS). CLU parcels are associated with a table of attributes; a landcover attribute field indicated landcover classification and a field called 3_CM was added in 2012, which indicates if a parcel has ever had a cropping history despite its current cover.	FSA 2014
National Land Cover Database (NLCD) -- Multi-Resolution Land Characteristics Consortium -- 2001, 2004, 2008, 2011, 2013, and 2016	2011 was used to identify bare, developed, and forested lands in the US for the PUDL layer. All years were used for grassland loss estimates in the US.	The NLCD is created by a partnership of federal agencies called the Multi-Resolution Land Characteristics Consortium. It is a 30 m resolution raster depicting broad landcover types that were classified using decision tree methods and Landsat imagery.	Homer et al. 2015
National Hydrologic Dataset (NHD) -- United States Geological Survey (USGS)	Used to remove large wetlands in the US for the PUDL layer.	NHD is a vector dataset that contains waterbodies mapped at a 1:24,000 scale or better. The dataset is updated and maintained through partnerships with state and collaborative bodies.	McKay et al. 2012

TIGER/Line -- U.S. Census Bureau	Used to remove roads and rails in the US for the PUDL layer.	Geospatial extracts from the U.S. Census Bureau's Master Address File/Topologically Integrated Geographic Encoding and Referencing database (MAF/TIGER). TIGER/Line shapefiles contain nationwide street centerline geospatial data in vector format. It was first released in 1989 and derived from United States Geologic Survey (USGS) Digital Line Graph (1:1,000,000-scale) and has been continually updated since then using data provided by partners from local, state, and federal governments.	TIGER/Line 2017
Land Use (LU) -- Agriculture Agri Foods Canada (AAFC) -- 1990, 2000, ad 2010	All years were used to identify disturbed lands in Canada for the PUDL layer and estimate grassland loss rates.	AAFC LU datasets are 30m landcover raster created using multiple data sources and a "preponderance of evidence" set of rules. It was created for all of Canada south of 60 degrees N and has overall accuracy assessment of 89.1%, 90.6%, and 94.7% for 1990, 2000, and 2010, respectively (if water and wetland classes are grouped together).	Download
Annual Crop Inventory (ACI) -- AAFC -- 2011-2017	All years were used to identify disturbed lands in Canada for the PUDL layer, and 2017 was used to identify and remove bare, developed, and forested areas. All years were used to estimate grassland loss rates.	AAFC ACI datasets are 30m rasters created using remote sensing data, training and testing data, and decision tree based classification methods. Radar data came from RADARSAT-2 (2011-2017), and optical data came from Landsat 5 (2011-2012), Landsat 8 (2013-2017), Sentinel-2 (2016-2017), and Gaofen-1 (2016-2017). These methods have produced overall accuracy for 2011-2017 cropland classes >= 85%.	Download

hydroLAKES -- World Wildlife Fund	Used to remove large wetlands in Canada and Mexico for the PUDL layer.	This is a global database that maps open water >= 10 ha as polygons. Sources to create this database vary by location. In Canada the dataset is produced from Canadian hydrographic dataset (CanVec; 1:50,000 scale, Natural Resources Canada 2013), Shuttle Radar Topographic Mission Water Body Data (1 arc-second raster, Slater et al. 2006), Global Lakes and Wetlands Database (1:1 million scale or better, Lehner and Doll 2004), Global Reservoir and Dam database (1:1 million scale or better, Lehner et al. 2011), and World Wildlife Fund mapping 1:1 million scale or better).	Messaner et al. 2018
National Road Network (NRN) -- Inter-Agency Committee on Geomatics	Used to remove roads and rails in Canada for the PUDL layer.	Prior to erasing these areas we buffered major roads by 25 m, and minor roads and rails by 15 m. The National Road and Rail Network databases are produced through intergovernmental partnerships that provide data updates at least once a year using a homogenous and standardized approach to represent centerline road phenomena at an approximate resolution of 1:10,000.	Download
Uso de suelo y vegetación (INEGI) -- Instituto Nacional de Estadística y Geografía -- 2002, 2007, 2011, 2014	All years were used to identify disturbed lands in Mexiso for the PUDL layer, and 2014 was used to identify and remove bare, developed, and forested areas. All years were used to estimate grassland loss rates.	INEGI uso de suelo y vegetation time-series landcover datasets, serie 3-6 are vector data produced from remote sensing imagery at a 1:250,000 scale. Serie 3-6 were produced using Landsat imagery from the following sensors and years: serie 3 used Landsat 7 ETM+ imagery from 2002, serie 4 used Landsat 5 imagery from 2007, serie 5 used Landsat 5 imagery from 2011, and serie 6 used Landsat 8 imagery from 2014.	(INEGI 2005, 2009, 2013, and 2016)

OpenStreetMap (OSM)	Used to remove roads and rails in Canada for the PUDL layer.	OpenStreetMap is an open source dataset built by a community of amateur to professional mappers using GPS, aerial imagery, or maps to add geospatial data to the OpenStreetMap database. Geofabrik processes these data using consistent and standardized methods, updates the datasets daily, and makes the data available for download as a shapefile (Ramm 2019; https://download.geofabrik.de/north-america/mexico.html).	www.openstreetmap.org
Cropland Data Layer (CDL) -- USDA, National Agricultural Survey Statistics (NASS) -- 2008-2018	All years were used to estimate grassland loss rates in the US.	Cropland Data Layer is produced at a 30 m resolution using Landsat imagery, training and testing data, and decision tree classification methods.	USDA NASS 2018
Conservation Areas Tracking System (CARTS) -- Canadian Council on Ecological Areas	Used to determine protected PUDL in Canada, and estimate 10-year average annual protection (2006-2015)	Vector dataset that catalogues protected area boundaries and their attributes such as type of protected area (federal, state, non-government, private, etc.) and the year of establishment.	Vanderkam 2017
Protected Area Database of the United States (PADUS) -- USGS	Used to determine protected PUDL in the US, and estimate 10-year average annual protection (2005-2014)	Vector dataset that catalogues protected area boundaries and their attributes such as type of protected area (federal, state, non-government, private, etc.) and the year of establishment.	USGS GAP 2018

World Database on Protected Areas (WDPA) -- United Nations Environment Programme (UNEP), International Union for Conservation of Nature (IUCN), UNEP World Conservation Monitoring Centre (UNEP-WCMC)	Used to determine protected PUDL in Mexico, and estimate 10-year average annual protection (2008-2017)	Vector dataset that catalogues protected area boundaries and their attributes such as type of protected area (federal, state, non-government, private, etc.) and the year of establishment.	UNEP-WCMC and IUCN 2018
Sentinel-2 Level-1C -- European Union Copernicus Program -- 2016-2018	Used for supervised classification across all regions.	Sentinel-2 is an earth observation mission that is part of the European Union Copernicus Program that collects orthoimagery by twin satellites. Level-1C products represent Top-of-the-Atmosphere reflectance in cartographic geometry. Images contain 13 bands including red, green, blue, and near infrared bands at 10m resolution, four red edge bands and two short-wave infrared bands at 20m resolution, and three bands that represent atmospheric quality at a 60m resolution. The satellites generate 100km^2 wide swath images with an approximate 5 day cadence.	
Multi-scale Topographic Index (MTPI)	Used for supervised classification across all regions.	MTPI is 270 m resolution index of topographic position derived from 30 m resolution Shuttle Radar Topography Mission digital elevation data (Theobald et al. 2015). Values range from negative (valleys) to positive (ridges).	Theobald et al. 2015

Appendix B: Workflow and Programming Code

PUDL Deductive Workflow

US –

Erased each year (2008-2011, 2013-2017) of clu classification code 3 and crop indicator code (3CM) 1 (starting in 2013) from the study extent polygon.

Extracted bare (code 31), developed (code 21-24), and forest (code 41-43) from NLCD 2011, converted to polygon, erased from extent.

Erased all NHD wetlands > 40 AC from the extent.

Buffered tiger dataset by 25 m for highways (mcff S1100, S1200), and 15 m for local roads (mcff S1400, S1630, S1640, S1720, S1730, S1740 S1750, S1780,) and rails, and then erased from the extent. Did not include tracks and trails (S1710, S1820, S1830).

CAN-

Used AAFC LU (1990, 2000, 2010, code 51) and ACI (2011-2017, codes 120 OR >= 130 AND <=199) to create a masking layer and masked crop from CI2017.

Then removed developed (code 34 and 35), bare (code 30), and forest (codes 200-230), and converted the raster to polygon.

Used WWF lakes >= 40 AC to remove large bodies of water.

Buffered the national road/rail network by 25 m (freeway, expressway/highway, arterial, rapid transit) and 15 m (rails, collector, local/street, local/strata, local/unknown, alleyway/lane, ramp, resource/recreation, service lane) and erased. Did not include winter roads.

MEX – RGJV

Removed crop from serie 6 (codes HA, RA, RAP RAS RP, RS, RSP, TA, TAP, TAS TP, TS), and erased serie 3, 4, and 5 crop from serie 6.

Removed bare (ADV, DV), developed (AH, ZU), foreign (P/E), and forest (BC, BS, BQ, BQP, BG, MK, BA BP, BPQ, BJ, BI, BM, VM, MKE, VPI, VPN, VSI, SBC, SBK, SG, SMS, SMQ, VSA/BS, VSA/BQ, VSA/BQP, VSA/MK, VSA/BP, VSA/BPQ, VSA/BM, VSA/VM, VSA/VPN, VSA/SBC, VSA/SBK, VSA/SBS, VSA/SMS, VSA/SMQ) from serie 6.

Removed WWF water greater than 40 AC.

Buffered OpenStreetMap major roads (5111 to 5115) by 25 m, and minor roads (5121 to 5144 and 5199) buffered by 15m and erased from serie 6. Tracks and trails were removed.

Loss Vs. Protection Landcover Codes

LU:

Cropland + developed codes: 21, 25, 51

Grass + shrub + wetland codes: 61, 62, 71, 73, 74

ACI:

Cropland + developed codes: 120, >=130 & <=199, 34, 35

Grass + shrub + wetland codes: 110, 122, 50, 80

CDL:

Cropland + developed codes: >=1&<=36, >=38&<=61,>=66&<=77, >=121&<=124, >=204&<=254

Grass + shrub + wetland codes: 176, 37, 64, 152, 87, 190, 195,

NLCD:

Cropland + developed codes: 82, >=21&<=24

Grass + shrub + wetland codes: 71, 81, 52, 90, 95

INEGI serie 5 and 6:

Cropland + developed codes: AH, ZU, HA, RA, RAP, RAS, RP, RS, RSP, TA, TAP, TAS, TP, TS

Grass + shrub + wetland codes: MC, MDM, MDR, MK, MKE, MKX, ML, MRC, MSC, MSCC, MSN, MST, PC, PH, PI, PN, VD, VG, VH, VHH, VSa/BB, VSa/BG, VSa/BJ, VSa/BP, VSa/BPQ, VSa/BQ, VSa/BQP, VSa/MC, VSa/MDM, VSa/MDR, VSa/MK, VSa/MKE, VSa/MKX, VSa/ML, VSa/MRC, VSa/MSC, VSa/MSCC, VSa/MSN, VSa/MST, VSa/PN, VSa/SBC, VSa/SBK, VSa/SMS, VSa/VD, VSa/VG, VSa/VH, VSa/VHH, VSa/VM, VSa/VPN, VSh/BJ, VSh/BP, VSh/BPQ, VSh/BQ, VSh/BQP, VSh/MDM, VSh/MRC, VSh/MSCC, VSh/MSN, VSh/SBC, VSh/SMS, VSh/VH, VSh/VM, VT, VU, PY, VY, VSh/MDR, VSh/MET, VSh/PN, MC, MET, MSM, VSa/VU, VSa/BS, VSa/MET, VSa/MSM, VSa/PY, VSa/PH

INEGI serie 3 and 4:

Cropland + developed codes: 10101010304, 10101040103, 10101040104, 10102010304, 10102040102, 10102040103, 10102040104, 10102040203, 10102040204, 10103040104, 30000000032, 30000000033

Grass + shrub + wetland codes: 10201040304, 20803010400, 20802010400, 21302030300, 20807070400, 21102010400, 20903010400, 20902010400, 20202020700, 20104020700, 20105020700, 20904020700, 20911020700, 20801020700, 20602020700, 20902020700, 20913030400, 20906010400, 20107010400, 20904010400, 20905010400, 20911010400, 20912010400, 20914010400, 20901010400, 20101020600, 20201020600, 20202020600, 21002020600, 21101020600, 20104020600, 20105020600

20106020600, 20913030600, 20906020600, 20904020600, 20905020600, 20911020600, 20912020600, 20914020600, 20803020600, 20802020600, 20801020600, 20602020600, 20701020600, 20901010600, 20902020600, 21007030400, 21005010400, 21009010400, 21005020600, 21009020600, 10201040304 , 20201020700 ,20501020700, 20908020700, 20909020700, 20910020700, 21003020700, 20102020600, 20501020600, 20603010400, 20603020600, 20703020600, 20907010400, 20907020600, 20908010400, 20908020600, 20909010400, 20909020600, 20910010400, 20910020600, 21003020600, 21103020600, 21006030400

Supervised Classification Training Data Indices

Red Edge Index

https://www.indexdatabase.de/db/si-single.php?sensor_id=96&rsindex_id=252)

Tasselled Cap Indices

https://www.indexdatabase.de/db/si-single.php?sensor_id=96&rsindex_id=564, https://www.indexdatabase.de/db/si-single.php?sensor_id=96&rsindex_id=91, https://www.indexdatabase.de/db/si-single.php?sensor_id=96&rsindex_id=93

Google Earth Engine Code

Estimating Loss Rates

CDL-US

https://code.earthengine.google.com/b60c6af4d203ea7b37e35319e12812eb

NLCD - US

https://code.earthengine.google.com/f2bdc8c27f1a28ef3282e9b4aee43cc1

LU and ACI – Canada

https://code.earthengine.google.com/f57f08ba636103b1d663bbb04706d994

Supervised Classification

NGPJV_NorthernGreatPlains_East

https://code.earthengine.google.com/2e1bff2b274abdb7bbfd3aa271e57e3c

NGPJV_NorthernGreatPlains_West

https://code.earthengine.google.com/e4fe5ab9a362cb901391c788384a7748

OPJV_BlacklandPrairie

https://code.earthengine.google.com/4b9220ea30a44d95479a15669b41c673

OPJV_Crosstimber

https://code.earthengine.google.com/4b9220ea30a44d95479a15669b41c673

OPJV_EdwardsPlateau

https://code.earthengine.google.com/a935406624303c7a777cbefd79e8f81b

PHJV_AspenParklands

https://code.earthengine.google.com/f9c70ad5ebe1d5f0f36e173daac88282

PHJV_MidBorealParklands

https://code.earthengine.google.com/b54d69a06f8362d99b0cfd75e2bd868b

PHJV_MidBorealUplands

https://code.earthengine.google.com/38ef1337dc16302fb970927958b5b69d

PHJV_NWGlaciatedPlains

https://code.earthengine.google.com/9a5cccdaff99b11c78ae7c88901eb3fc

PLJV_CentralGreatPlains

https://code.earthengine.google.com/f834ba7f095e04937c4c701c9c0ed0e1

PLJV_HighPlainsTableLands_North

https://code.earthengine.google.com/3fc5bf4bc683e71c05510c2d2acf40e2

PLJV_HighPlainsTableLands_South

https://code.earthengine.google.com/ab1edb680fc26fcd2d423256c386e605

PPJV_AgassizPlains

https://code.earthengine.google.com/abb89717deddfbc98cc18149d8190bf5

PPJV_GlaciatedPlains

https://code.earthengine.google.com/fa25b72f4e078479bae2bd82887d5cca

PPJV_NWGlaciatedPlains

https://code.earthengine.google.com/e3783c7b629b3a313fb907bab65a1e88

PPJV_WesternCornBelt

https://code.earthengine.google.com/e2b6b430d179f9a0bf6f9581f19a5969

RBJV_Rainwaterbasin

https://code.earthengine.google.com/1a633972d801922e8bcd8bd5ed4a0ce9

RGJV_ChihuahuanGrasslands_North

https://code.earthengine.google.com/b6575f9dcd0f9e6429a7c9365be87501

RGJV_ChihuahuanGrasslands_South

https://code.earthengine.google.com/dcdb1082bb1bf8fafac2aa83320c7023

RGJV_InteriorPlainsXeroScrub

https://code.earthengine.google.com/c51fd428cb4b7f84d8981bdd37114fef