SORGHUM LAND COVER / USE CONVERSION AND RISK ASSESSMENT

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SORGHUM CHECKOFF

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EXECUTIVE SUMMARY

To address concerns about the impact of deforestation and land conversion on key ecosystems, standards and requirements have been developed to certify that plant-based ingredients are sourced from deforestation and conversion-free (DCF) supply chains. One such standard is the Aquaculture Stewardship Council's (ASC) Feed Standard that requires feed mills to conduct due diligence (DD) on their plant-based raw materials. Under this process, feed mills sourcing plant-based ingredients from the United States are required to conduct DD to ensure the absence of risk for legal deforestation / conversion within their supply chains.

The United Sorghum Checkoff Program has produced this report to provide industry stakeholders with solid evidence of the low risk of U.S.-sourced DCF sorghum-derived ingredients across multiple uses. This effort consists of two tasks – (1) the characterization of land cover and land use in the United States; and (2) an assessment of the risk of legal deforestation / conversion in the United States in relation to sorghum production. The robust risk assessment of legal deforestation / conversion, aligned with ASC's DD requirements for feed ingredient certification, indicates that **the United States is at 'low-risk' for legal deforestation / conversion at sub-national and national levels**.

The first task - characterization of land cover and land use - creates new and unique Baseline and Change Detection Data Layers using a new geospatial dataset from the U.S. Geological Survey (USGS) called the Annual Land Cover Database (ANLCD). The first data layer is a baseline of natural forest and grassland across the contiguous United States between 1985 through 2007. The Change Detection Layer maps conversion of natural forest and grassland to cropland from 2008 through 2022. The U.S. Department of Agriculture's (USDA) Cropland Data Layer (CDL) is then used to create an additional layer to the Change Detection Layer by assigning identity to cropland in sorghum production that was converted from natural forests and grasslands. Baseline and conversion hectares are reported for Farm Resource Regions (FRRs) - sub-national areas defined and used by the USDA - and at the U.S. national level.

The second task – risk assessment of legal deforestation / conversion – develops methodology aligned with ASC's DD sub-national / sector assessment pathway. This involves leveraging the unique and accurate georeferenced assessment of natural forest and grassland conversion to cropland, in general, and to sorghum, specifically. Six robust and timely risk indicators are defined, risk levels (low, medium and high) are assigned to the risk indicators (based on the geospatial-based mapping results), and aggregated Natural Forest and Natural Grassland Risk Scores and a Composite Legal Deforestation / Conversion Risk Score are calculated and reported for FRRs and at the U.S. national level.

While this analysis generates robust and scientifically-based evidence of low deforestation / conversion trends in the United States as of 2022, the threats to key ecosystems and the climate are ongoing. The United Sorghum Checkoff Program is committed to ongoing and transparent monitoring and measurement of natural forest and grassland conversion to sorghum to ensure that the reliance on plant-based ingredients is not at the detriment to the ecosystems everyone strives to preserve. Continuous monitoring of conversion trends will be done to validate the continued low rate of deforestation and grassland in the United States, ensuring that sorghum-derived ingredients are a key part of modern and sustainable feed and protein production.

1. INTRODUCTION

Sorghum-derived ingredients are affordable and globally available and can be a key part of modern and sustainable feed and protein production. However, industry stakeholders are often concerned about the impacts that plant-based ingredients can have on increasing deforestation and land conversion on key ecosystems and the climate. To help address these concerns, public and private stakeholders, including international industry organizations, have developed standards and requirements with which ingredient suppliers must comply. These apply to producers of key inputs in feed formulations, such as sorghum and sorghum-derived feed ingredients, and encompass specific sustainability criteria such as assurances of deforestation and conversion-free (DCF) supply chains.

While the demand for DCF sorghum-derived ingredients spans numerous industries, the aquaculture industry has been at the forefront of requiring certification of DCF ingredients. Plant-based ingredients have been growing in importance within aquaculture feed manufacturing over many years, due to their cost-effectiveness, nutritional value, and relative higher sustainability when compared with other sources of nutrients, allowing for tailored diets, thereby enhancing fish species growth and health. Plant-based ingredients such as sorghum-derived products (sorghum meal, sorghum grits, sorghum protein concentrate, etc.) reduce reliance on animal-based protein sources such as fishmeal, easing pressure on wild fish stocks and reducing environmental impacts.

However, due to the high usage of certain plant-based ingredients such as soybean meal and palm oil, which have been linked to negative impacts of sensitive ecosystems in some of the countries in which they are produced (e.g., Brazil and Indonesia), aquaculture standards have moved to require aquafood and feed producers to provide assurances related to these environmental impacts within their supply chains. As such, assurances of DCF sourcing have been established as sustainability requirements for plant-based feed ingredients across aquaculture feed and farm standards.

Examples of such standards include those managed by the Aquaculture Stewardship Council (ASC), the Global Seafood Alliance's Best Aquaculture Practices (GAA-BAP), and GLOBALG.A.P.'s Compound Feed Manufacturing standard. To align with standard requirements for DCF ingredients, feed manufacturers are often mandated to go through a due diligence (DD) reporting process for any supply chain ingredient that constitutes a significant share of their final product (shares range between 1% to 5%).

In particular, the "ASC Feed Standard" requires feed mills to conduct DD on their marine and plant-based raw materials, including risk of legal deforestation and (grassland) conversion. Under this process, the ASC Feed Standard has designated the United States as a 'medium-risk' country for legal deforestation / conversion; this means that feed mills sourcing plant-based ingredients from the United States are required to provide specific assurances for individual ingredients to ensure the absence of risk for legal deforestation / conversion within the feed manufacturer's supply chain.

The designation of the United States as a 'medium-risk' country for legal deforestation / conversion associated with crop production is counter to the best available evidence, as reported by the U.S. Department of Agriculture (USDA)[1]. However, given the importance of this issue to the users of U.S. sorghum and sorghum-derived products, and their need to comply with the standards that enable their participation in key markets, the United Sorghum Checkoff Program has moved to produce this report. The purpose of this effort is to provide industry stakeholders with solid evidence that U.S.-sourced sorghum-derived ingredients across multiple end-uses are 'low-risk' for legal deforestation / conversion.

To accomplish this task, this report is structured and executed to provide two key deliverables:

1. A first-of-its-class characterization of land cover and land use in the United States, leveraging a new geospatial data product published by the U.S. Geological Survey (USGS) (the Annual National Land Cover Data- ANLCD). The ANLCD allows for the development of two unique georeferenced data layers – a Baseline Layer and a Change Detection Layer – to achieve (i) an accurate baseline of natural forest, natural grassland and cropland area in the United States, and (ii) an accurate assessment of the extent of conversion of natural forest and natural grassland to cropland and to cropland with a sorghum footprint (utilizing the U.S. Department of Agriculture National Agricultural Statistics Service's (USDA/NASS) Cropland Data Layer- CDL).
2. An assessment of the risk of legal deforestation and grassland conversion in the United States in relation to sorghum production; this assessment is in alignment with the DD requirements for feed ingredient certification as established by ASC, under its feed ingredient standard and the criteria for legal deforestation / conversion.

The first section of this report describes the methodology and results from the geospatial-based mapping of U.S. natural forest, natural grasslands, and cropland, with the georeferenced data layers providing a first-of-its kind location-specific historical assessment of land cover and land use. While these data layers form the foundation of the analysis conducted to meet the second deliverable of this project, they also have potential

[1] USDA Assessment of Ag-driven deforestation: https://www.usda.gov/sites/default/files/documents/USDA-Assessment-of-Ag-driven-Deforestation.pdf

wide-spread use for all domestic and international stakeholders interested in better understanding deforestation and grassland conversion in the United States.

An overview of ASC's DD requirements for assessing the risk of legal deforestation / conversion is then presented. The methodology developed for the risk assessment for legal deforestation / conversion using the geospatial-based mapping results is described, followed by the risk assessment results at the U.S. national and sub-national (Farm Resource Region) levels. Plans for ongoing monitoring and planned updates are explained, and concluding remarks are presented. Supplemental information, including references, a list of abbreviations, a glossary of key terms, a technical summary of the geospatial-based land cover / land use change (LCLUC), and qualifications of the analysts, complete the report.

2. GEOSPATIAL-BASED MAPPING OF U.S. NATURAL FOREST, NATURAL GRASSLAND AND CROPLAND

2.1. DATA AND LAND COVER / LAND USE CLASSES

BACKGROUND ON DEFORESTATION AND CONVERSION SOURCES

The ASC designation of the United States as a 'medium-risk' level country for legal deforestation / conversion relies on two key data sources – the Global Forest Watch (GFW) data[2] on natural forest cover and deforestation driven by permanent agriculture, and the World Wildlife Fund's (WWF) Plowprint report[3].

The methodology[4] behind the GFW forest cover data, described in Potapov, et al. (2022), relies on locally and regionally calibrated machine learning tools applied to satellite imagery to classify land cover and land use (LCLU) for a global map. This machine learning approach produces estimates of land cover and land use, not actual classification of each unit of area (typically referred to as pixel in geospatial analysis). In addition, the classification of each pixel is based on a single year of information which can be misleading and generate errors in classification of pixels.

In terms of risk assessment of grassland conversion, ASC designates a country as being 'high-risk' for (grassland) conversion if the country is mentioned in the Plowprint report. In the 2024 Plowprint report, the United States and Canada are the only countries discussed in the report, therefore automatically classifying them as 'high-risk' for grassland conversion.

[2]https://www.globalforestwatch.org/
[3]https://www.worldwildlife.org/places/great-plains/plowprint-report/
[4]https://gfr.wri.org/data-methods#methodology

The Plowprint report uses USDA/NASS's Cropland Data Layer[5] (CDL) for its assessment of grassland conversion to cropland, which researchers have acknowledged present problems when using it to assess LCLUC. The problems stem from various issues including disparate CDL datasets, the ability to distinguish between land cover and land use or grassland types, and CDL accuracies using satellite imagery. The dissimilarities in the CDLs are caused by several factors including changes over time in satellite imagery resolution, validation and training data, and CDL methodology.

Characterizing any specific land area as moving from grassland to cropland depends on prior grassland use and management practices; single-year satellite images do not show either prior grassland use or management practices (Lewandrowski, et al., 2020). USDA/NASS (USDA-NASS-CDL, 3/05/2020) states that the strength and emphasis of the CDL is its crop-specific land cover categories. The accuracy of the CDL non-agricultural land cover classes (such as grassland) is entirely dependent upon the USGS National Land Cover Database (NLCD). Thus, USDA/NASS recommends that users consider the NLCD for studies involving non-agricultural categories and grassland/pasture categories.

Due to the technical challenges and limitations presented above, many agricultural stakeholders have expressed their inconformity with the characterization of LCLU provided by the Plowprint report. The present assessment aims to provide a more refined and accurate characterization of LCLU dynamics in relation to sorghum production areas in the United States.

AVAILABILITY OF NEW DATA

The availability and accuracy of satellite imagery for LCLU mapping have increased dramatically in recent years. In September 2024, the USGS released a new data product called the Annual National Land Cover Database[6] (ANLCD) consisting of nationwide georeferenced data starting in 1985. This unique and annual dataset provides land cover and land change information using consistent satellite imagery and LCLU classifications over several decades, something that has not been previously available.

This study leverages ANLCD's unique features to map a "baseline" of land cover across the United States for a specific time (for this analysis, the baseline is established from 1985 through 2007), and to assess LCLUC over time (for this analysis, the change assessment period is from 2008 through 2022).

To supplement the ANLCD mapping, the CDL is used to map cropland area converted from natural forest or natural grassland on which sorghum has been part of the crop rotation beginning in 2008. The CDL is utilized due to it being an annual georeferenced, crop-specific

[5]https://www.nass.usda.gov/Research_and_Science/Cropland/SARS1a.php
[6]https://www.usgs.gov/centers/eros/science/annual-national-land-cover-database

land cover data layer produced using satellite imagery and extensive agricultural ground reference data.

LAND COVER / LAND USE CLASSES

For this study, each unit of area or pixel in the ANLCD and CDL datasets is assigned a land cover / land use class for the mapping of LCLUC. The ANLCD uses a modified Anderson Level II classification system with 16 land cover classes. To meet the needs of this mapping analysis, applicable land cover classes in the ANLCD are aggregated and defined. The unique land cover / land use classes defined for this analysis are "Natural Forests", "Non-natural Forests", "Natural Grasslands" and "Non-natural Grasslands" (Note: see Side Bar for the definitions). The definitions are guided by the Accountability Framework initiative's (AFi) definitions[7] for Forest and Natural Forest.

Figure 1 illustrates the mapping of the ANLCD land cover classes to the classes defined for this analysis. The three ANLCD Forest classes (Deciduous, Evergreen and Mixed) are aggregated and then categorized for the Baseline as either Natural Forest or Non-natural Forest, based on their history of cultivated agricultural activity during the 1985 – 2007 timeframe.

The distinction between Natural and Non-natural Forest and between Natural and Non-natural Grassland (described below) is an important and foundational component of this geospatial analysis. The multi-year spectral profiles allow for detection of any cultivated agricultural activity across many years, indicating that if agricultural activity is detected, the pixel does not possess many or most of the characteristics of a forest or grassland native to the given area, and therefore would be considered Non-natural Forest or Non-natural Grassland. Thus, the classification of Natural Forest and Natural Grassland increases the likelihood of correct classification of natural or native forest and grassland. Pixels classified as Non-natural Forest and Non-natural Grassland are not analyzed for conversion to cropland for this analysis due to their history of some cultivated agricultural activity occurring between 1985 and 2007.

LAND COVER / USE CLASSES

Natural Forests

Land with forest cover that possess many or most of the characteristics of a forest native to the given site, including species composition, structure and ecological function; includes primary forests, regenerated forests, managed natural forests and degraded forests, which during the 1985 –2007 timeframe had no cultivated agricultural activity.

Non-natural Forests

Land with forest cover that at any time during the 1985 –2007 timeframe showed cultivated agricultural activity.

Natural Grasslands

Herbaceous, shrubs, and pasture/hay land cover that possess many or most of the characteristics of grasslands native to the given site, including species composition, structure and ecological function. This includes primary grasslands, regenerated grasslands, managed natural grasslands and degraded grasslands, which during the 1985 – 2007 timeframe had no cultivated agricultural activity.

Non-natural Grasslands

Land with grassland cover (herbaceous, shrubs, and pasture/hay) that at any time during the1985 – 2007 showed cultivated agricultural activity.

[7] https://accountability-framework.org/the-accountability-framework/definitions/

Mapping long-term changes in grassland types is difficult to do for many reasons, including the complexity and diversity of grassland types (Zhang, et al. 2024). Consequently, it is difficult to differentiate grassland types using single spectral information (Hou, et al. 2023). Two approaches are adopted with the geospatial-based LCLU mapping implemented for this study to address these challenges. The first is the trajectory-based approach, while the second approach is the LCLU classes considered for grasslands.

Three ANLCD herbaceous-based classes - Shrubland, Herbaceous, and Planted / Cultivated: Pasture / Hay – are considered Grasslands for this study. The strength of the trajectory-approach used for this analysis is that it detects any cultivated agricultural activity over the pixel's temporal profile, and if agricultural activity is detected during the timeframe, the pixel is classified as "non-natural". Therefore, if any agricultural activity (i.e., cultivation) is detected from 1985 through 2007 on the pixel classified by ANLCD as Pasture / Hay, the same pixel would be classified as Non-natural and would not be included in the conversion of Natural Grassland to Cropland. The Pasture / Hay pixels classified as Natural Grassland had no agricultural activity detected on them from 1985 through 2007.

GRASSLAND CLASSES

Shrubland

Areas dominated by shrubs less than 5 meters tall with shrub canopy typically greater than 20% of total vegetation. This class includes true shrubs, young trees in an early successional stage or trees stunted from environmental conditions.

Herbaceous / Grassland

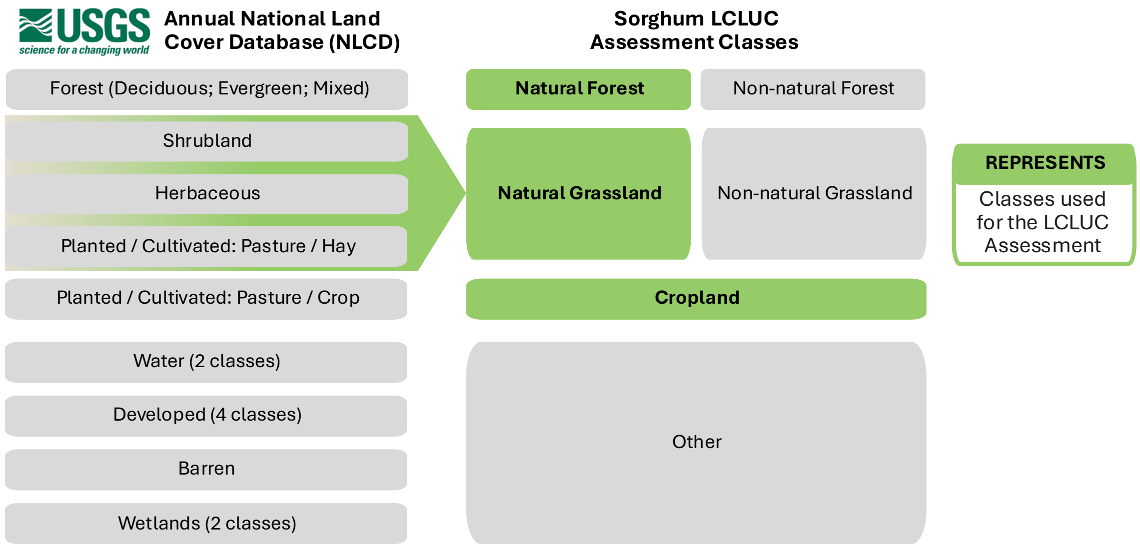
Areas dominated by graminoid or herbaceous vegetation, generally greater than 80% of total vegetation. These areas are not subject to intensive management such as tilling but can be utilized for grazing.

Pasture / Hay

Areas of grasses, legumes or grass-legume mixtures planted for livestock grazing or the production of seed or hay crops, typically on a perennial cycle. Pasture / hay vegetation accounts for greater than 20% of total vegetation.

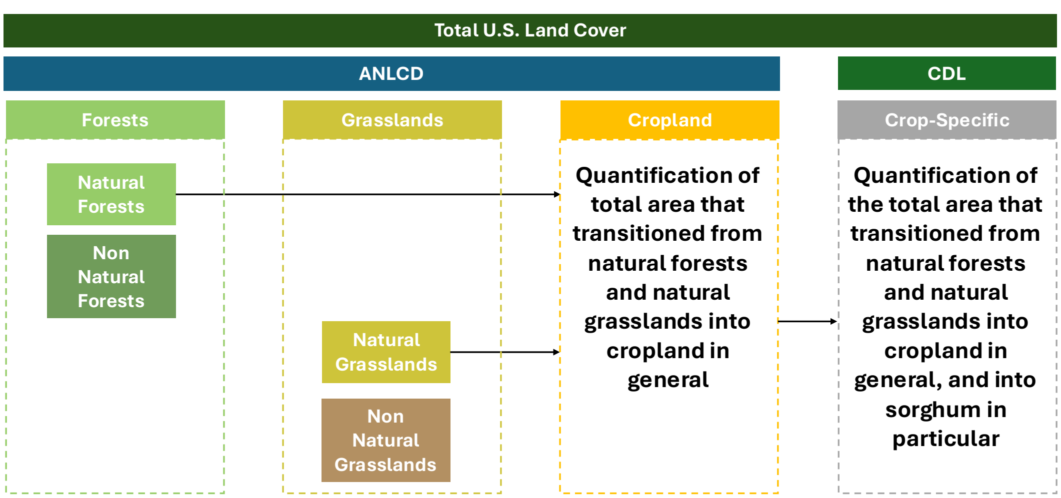
Similarly to the forest classes, the Shrubland, Herbaceous and Pasture / Hay classes are aggregated and categorized for the Baseline as either Natural Grasslands or Non-natural Grasslands. Since the objective of this analysis is to assess the conversion of natural forests and natural grasslands to cropland, the remaining classes (Water, Developed, Barren and Wetlands classes) are aggregated into a general "Other" land cover class. This aggregated Other class is not part of the assessment of Natural Forest and Natural Grassland conversion to Cropland.

Figure 1. ANLCD and Sorghum LCLUC Assessment Classes



The ANLCD does not distinguish the crop type for the pixels classified as "Cultivated Crops." However, the CDL uses over 110 agricultural classes and 14 non-agricultural classes in its data product, with high Producer's Accuracy (85 to 95%) for major crop-specific land cover classes[8]. Each pixel classified as "agriculture" is assigned to a specific crop class such as "sorghum" on an annual basis. Therefore, CDL users can identify land area (pixels) on which sorghum is grown for a specific year. As a result, land area that has been converted from Natural Forest or Natural Grassland to Cropland (via the ANLCD mapping) can subsequently be identified as having sorghum part of the cropping system on that area, simply referred to as conversion to sorghum. This is accomplished by supplementing the ANLCD mapping with CDL data (Figure 2).

Figure 2. Geospatial-based LCLC Mapping Using the ANLCD and CDL



[8]https://www.nass.usda.gov/Research_and_Science/Cropland/sarsfaqs2.php#:~:text=ACCURACY:%20The%20accuracy%20of%20the,crop%2Dspecific%20land%20cover%20categories.

2.2. METHODOLOGY

The geospatial-based LCLU mapping employed for this study is conducted in the following order (summarized in Figure 3):

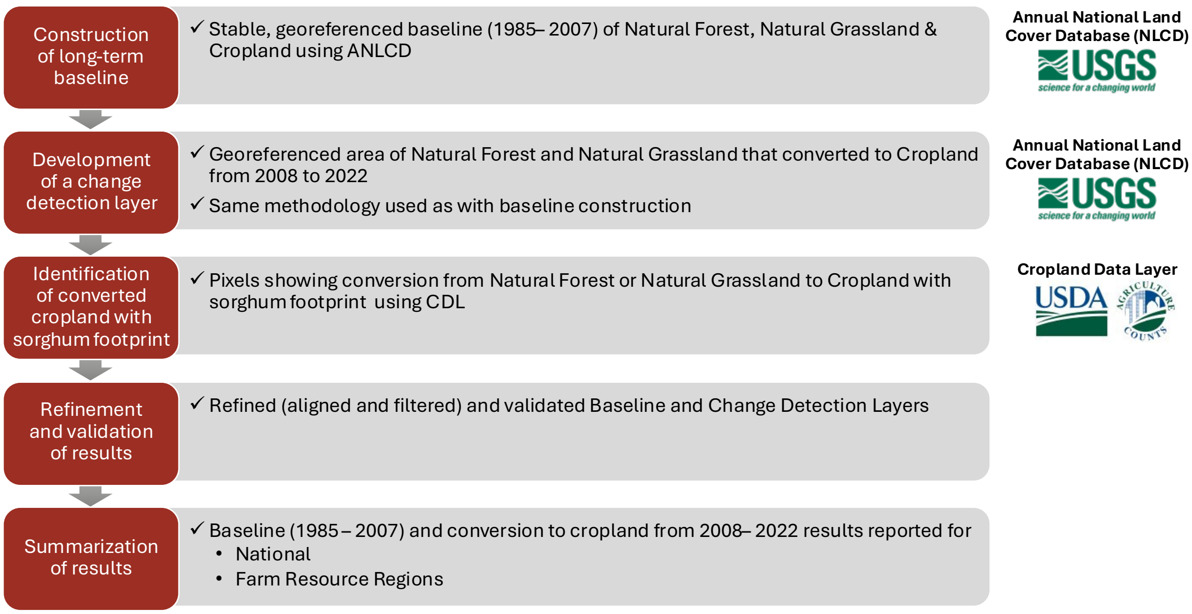
1. The long-term base layer (Baseline layer) is constructed to support post-2007 LCLUC assessments:
    a. The contiguous United States is mapped, using the ANLCD, to create a stable, georeferenced Baseline (1985 – 2007) of natural forest, natural grassland and cropland area as of 2007.
    b. To capture longer-term patterns of LCLU, a trajectory-based analysis using multi-year windows (1 three-year and 4 five-year intervals) categorizes each pixel as being either consistent or intermittent in its LCLU class over the 1985 – 2007 timeframe.
    c. Pixels classified as Forest or Grassland are further classified as Natural Forest or Non-natural Forest, or Natural Grassland or Non-natural Grassland, depending on whether they have consistent or intermittent classification from 1985 to 2007.
2. A Change Detection Layer is developed for 2008 through 2022:
    a. A similar approach is used to develop a Change Detection Layer from 2008 through 2022 as with the construction of the Baseline using the ANLCD. The Change Detection Layer identifies georeferenced area of Natural Forest and Natural Grassland that converted to cropland across the contiguous United States from 2008 through 2022.
    b. Developing the Change Detection Layer includes a trajectory-based analysis utilizing three 5-year windows to detect the timing and persistence of transitions from Natural Forest or Natural Grassland to Cropland. Therefore, any pixels that show conversion of either Natural Forest or Natural Grassland to Cropland are assigned an “ag-footprint” designator for robust understanding of the impact of prior history on the conversion pixels.
3. Converted cropland area with a sorghum footprint from 2008 through 2022 is identified:
    a. The CDL (2008 – 2022) is used to assign crop identity to the pixels showing conversion from Natural Forest and Natural Grassland to Cropland (identified in the Change Detection Layer developed in the previous step). Any conversion pixel with at least one year of sorghum presence is classified as having a sorghum footprint.
    b. This step creates an additional layer to the Change Detection Layer.

4. The results are refined using logical refinement, temporal alignment, spatial filtering and Minimum Mapping Unit (MMU) enforcement.

5. The LCLU conversions are validated via confidence and cross-dataset analyses.

6. The conversion patterns are summarized across spatial (FRRs) and temporal scales.

Figure 3. Overview of Geospatial-based LCLU Mapping



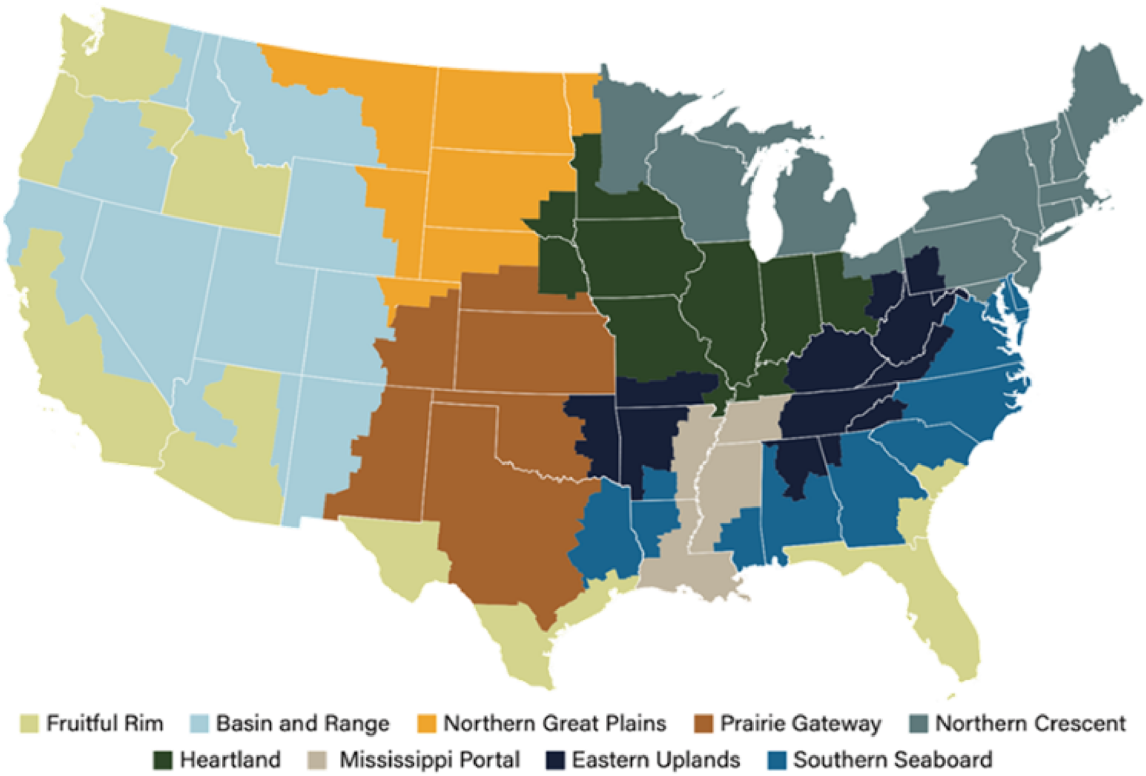
This geospatial analysis produces two different Geographic Information System (GIS) layers for the contiguous United States – a stable, long-term Baseline Layer (1985 – 2007), and a Change Detection Layer detecting conversion of Natural Forest and Natural Grassland to cropland, in general, and to sorghum, specifically, spanning 15 years (2008 through 2022). These georeferenced data layers are unique and enable georeferenced analyses of conversion of natural landscapes to cropland and specifically to areas with sorghum production.

The technical details of the geospatial-based LCLU mapping methodology are described in the Appendix.

REPORTING OF BASELINE AND CONVERSION RESULTS

The baseline and conversion results are reported at the Farm Resource Region (FRR) level (Figure 4) and at the U.S. national level. FRRs are used by the USDA and are derived from four sources: a cluster analysis of U.S. farm characteristics, the old Farm Production regions, USDA's Land Resource Regions (LRRs), and NASS Crop Reporting Districts (CRDs). The FRRs contain areas with similar types of farms intersecting with areas of similar physiographic, soil, and climatic traits as reflected in the LRRs. These intersecting areas follow the boundaries of NASS CRDs, which are aggregates of counties, incorporating some level of simple jurisdictional boundaries but relying more so on environmental factors that may dictate tendencies of LCLUC.

Figure 4. USDA ERS Farm Resource Regions



Source: USDA, Economic Research Service Farm Resource Regions.

2.3. U.S. RESULTS: GEOSPATIAL-BASED LAND COVER / LAND USE MAPPING

The Baseline and Change Detection Data Layers, augmented with information on cropland with a sorghum footprint, provide georeferenced data on U.S. natural forests, natural grasslands, and cropland baselines, and conversion to cropland, in general, and to sorghum, specifically, that have not been available before.

The "trajectory-based" approach used to create these data layers incorporates the rich history of land cover and land use that the ANLCD uniquely provides, resulting in robust data layers that industry stakeholders can use to understand baseline areas for natural forests, natural grasslands and cropland and conversion of the natural landscapes to cropland.

While the geospatial-based LCLU mapping generates more results than presented in this report, the following sections focus on the conversion of Natural Forests and Natural Grasslands to cropland, in general, and to sorghum, specifically. These results provide the necessary data for the ASC risk assessment of legal deforestation / conversion described in the following sections.

NATURAL FOREST CONVERSION IN THE UNITED STATES

> ***Conclusion:*** *Baseline Natural Forest converted to sorghum production in the United States from 2008 through 2022 was an estimated 1,178 hectares. This constitutes a share of 0.001% of the total U.S. natural forest area of 191,124,845 hectares, or an annual conversion rate of 0.0001%. This demonstrates a minuscule rate of deforestation of Natural Forest into sorghum production in the United States.*

According to USDA data, U.S. forest area has been stable in recent years and U.S. agricultural production is not driving deforestation that has been occurring[9]. In fact, USDA reported that the largest gains in forest in area have been reversions of agricultural land into forest, and that since 2010, forest carbon stocks in the United Sates have increased by nearly 2,000 MMT C (3.6%). Global Forest Watch's data indicate that between 2008 and 2022 (the years of change considered for this analysis), permanent agriculture-driven deforestation consisted of only about 4% of total tree cover loss and showed a downward trend in the U.S [10].

[9]USDA Assessment of Ag-driven deforestation: https://www.usda.gov/sites/default/files/documents/USDA-Assessment-of-Ag-driven-Deforestation.pdf
[10]https://www.globalforestwatch.org/dashboards/country/USA/?map=eyJjYW5Cb3VuZCI6dHJ1ZX0%3D

In this study, the Natural Forest Baseline (1985 – 2007) and conversion of Natural Forest to cropland, in general, and sorghum, specifically, from 2008 through 2022 are shown in Table 1. The number and share of hectares of Natural Fores converted to sorghum were minuscule. While the Southern Seaboard experienced the greatest number of hectares (only 661 hectares) of conversion to sorghum during that timeframe, the conversion as a share of Baseline Natural Forest was the largest in the Prairie Gateway FRR. However, the proportion of Baseline Natural Forest that was converted to sorghum spanning from 2008 through 2022 across all FRRs was less than or equal to 0.003%. Nationally, only 0.001% of the Natural Forest Baseline was converted to sorghum during those 15 years.

Table 1. Natural Forest Baseline and Conversion by Farm Resource Region (Hectares)

		Natural Forest Baseline		Conversion of Natural Forest Baseline to Cropland		Conversion of Natural Forest Baseline to Sorghum	
USDA Farm Resource Region	Total Area	Hectares	Share of Total Area (%)	Hectares	Share (%)	Hectares	Share (%)
Basin and Range	164,750,702	42,405,296	25.7	142	0.00	0	0.000
Fruitful Rim	125,635,014	24,779,540	19.7	29,869	0.12	120	0.000
Prairie Gateway	107,537,383	7,278,621	6.8	6,898	0.09	205	0.003
Northern Great Plains	75,971,946	2,969,258	3.9	1,265	0.04	0	0.000
Southern Seaboard	65,155,176	27,331,396	41.9	93,893	0.34	661	0.002
Northern Crescent	85,306,539	37,226,757	43.6	25,085	0.07	48	0.000
Mississippi Portal	26,680,719	6,379,274	23.9	4,709	0.07	41	0.001
Eastern Uplands	53,178,584	31,511,165	59.3	6,508	0.02	58	0.000
Heartland	74,549,487	11,243,539	15.1	33,675	0.30	43	0.000
U.S. Total	**778,765,550**	**191,124,845**	**24.5**	**202,043**	**0.11**	**1,178**	**0.001**

NATURAL GRASSLAND CONVERSION IN THE UNITED STATES

> ***Conclusion:*** *Baseline Natural Grassland converted to sorghum production in the United States from 2008 through 2022 was an estimated 114,256 hectares. This constitutes a share of 0.04% of the total U.S. natural grassland area of 322,863,638 hectares, or an annual conversion rate of 0.002%. This demonstrates a minuscule rate of conversion of Natural Grasslands to sorghum production in the United States.*

Natural Grasslands constitute the largest land cover class in the United States, and of the three grassland classes, Shrubland covers the largest share of total Natural Grasslands. Table 2 summarizes the Baseline and conversion to cropland, in general, and to sorghum, specifically, between 2008 and 2022, disaggregated into the three grassland classes – Shrubland, Herbaceous and Pasture/Hay.

While the Prairie Gateway had the largest number of Natural Shrubland and Herbaceous hectares converted to sorghum of the nine FRRs, the converted areas were only 0.05% of the total Natural Shrubland Baseline and only 0.21% of the Natural Herbaceous Baseline for that FRR. The largest number of Natural Pasture / Hay hectares converted to sorghum was in the Fruitful Rim FRR.

Table 2. Natural Shrubland, Herbaceous and Pasture/Hay Conversion by Farm Resource Region (Hectares)

USDA Farm Resource Region	Natural Shrubland Baseline	Conversion of Natural Shrubland Baseline to Cropland		Conversion of Natural Shrubland Baseline to Sorghum		Natural Herbaceous Baseline	Conversion of Natural Herbaceous Baseline to Cropland		Conversion of Total Natural Herbaceous to Sorghum		Natural Pasture/Hay Cover Baseline	Conversion of Natural Pasture / Hay Baseline to Cropland		Conversion of Total Natural Pasture / Hay to Sorghum	
		Hectares	Share (%)	Hectares	Share (%)		Hectares	Share (%)	Hectares	Share (%)		Hectares	Share (%)	Hectares	Share (%)
Basin and Range	91,218,049	74,933	0.08	760	0.00	12,717,113	76,314	0.60	198	0.00	1,473,896	56,378	3.83	278	0.02
Fruitful Rim	51,457,920	66,321	0.13	3,282	0.01	10,924,265	124,992	1.14	223	0.00	4,403,168	121,170	2.75	7,620	0.17
Prairie Gateway	29,433,401	87,246	0.30	15,152	0.05	28,036,885	399,572	1.43	59,680	0.21	4,879,650	108,316	2.22	3,816	0.08
Northern Great Plains	7,347,356	6,325	0.09	86	0.00	32,343,308	473,505	1.46	14,780	0.05	1,758,495	222,807	12.67	2,790	0.16
Southern Seaboard	2,285,802	7,975	0.35	41	0.00	1,769,581	8,279	0.47	66	0.00	8,007,744	114,920	1.44	1,553	0.02
Northern Crescent	911,212	1,547	0.17	9	0.00	980,484	13,487	1.38	157	0.02	5,843,776	319,087	5.46	167	0.00
Mississippi Portal	552,689	283	0.05	1	0.00	291,943	196	0.07	1	0.00	2,802,025	85,573	3.05	1,039	0.04
Eastern Uplands	425,696	181	0.04	0	0.00	1,220,017	818	0.07	20	0.00	11,895,518	276,412	2.32	575	0.00
Heartland	22,413	709	3.16	0	0.00	829,903	87,609	10.56	60	0.01	9,031,331	856,014	9.48	1,903	0.02
U.S. Total	**183,654,537**	**245,519**	**0.13**	**19,331**	**0.01**	**89,113,499**	**1,184,772**	**1.33**	**75,185**	**0.08**	**50,095,602**	**2,160,676**	**4.31**	**19,740**	**0.04**

Table 3 presents the Natural Grassland Baseline (1985 – 2007) and conversion to cropland and to sorghum between 2008 and 2022. The Prairie Gateway FRR experienced the largest number of total Natural Grassland hectares converted to sorghum, yet the converted area was only 0.13% of the Natural Grassland Baseline.

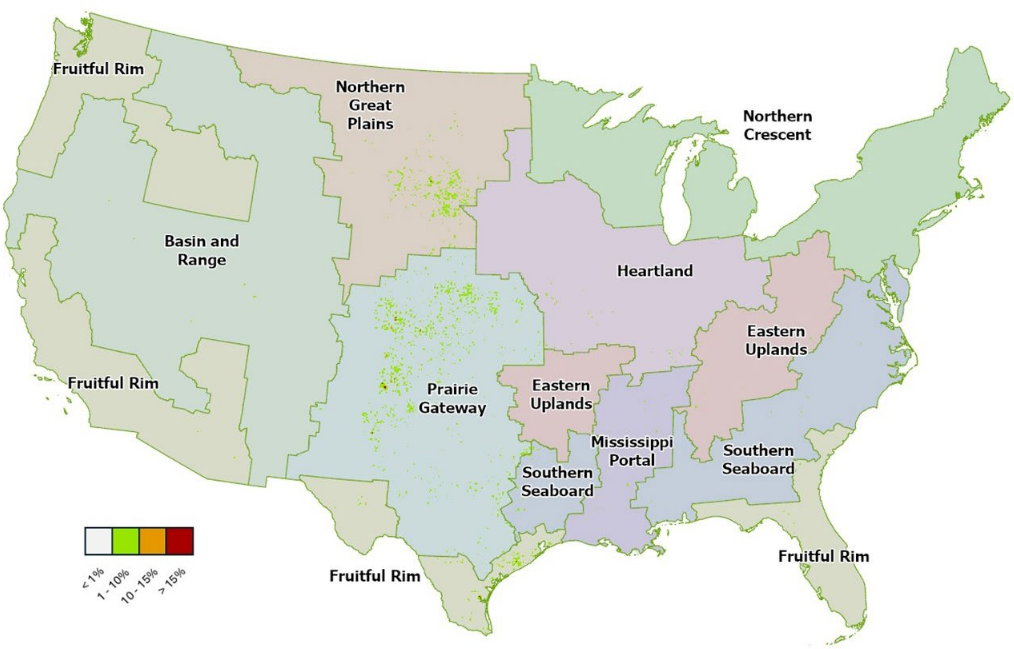
Table 3: Natural Grassland Baseline and Conversion by Farm Resource Region (Hectares)

USDA Farm Resource Region	Total Area	Natural Grassland* Baseline		Conversion of Natural Grassland* Baseline to Cropland		Conversion of Natural Grassland* Baseline to Sorghum	
		Hectares	Share of Total Area (%)	Hectares	Share (%)	Hectares	Share (%)
Basin and Range	164,750,702	105,409,058	64.0	207,624	0.20	1,235	0.00
Fruitful Rim	125,635,014	66,785,353	53.2	312,484	0.47	11,125	0.02
Prairie Gateway	107,537,383	62,349,936	58.0	595,133	0.95	78,648	0.13
Northern Great Plains	75,971,946	41,449,159	54.6	702,636	1.70	17,656	0.04
Southern Seaboard	65,155,176	12,063,126	18.5	131,174	1.09	1,659	0.01
Northern Crescent	85,306,539	7,735,473	9.1	334,120	4.32	332	0.00
Mississippi Portal	26,680,719	3,646,656	13.7	86,052	2.36	1,041	0.03
Eastern Uplands	53,178,584	13,541,231	25.5	277,411	2.05	596	0.00
Heartland	74,549,487	9,883,647	13.3	944,332	9.55	1,963	0.02
U.S. Total	**778,765,550**	**322,863,638**	**41.5**	**3,590,967**	**1.11**	**114,256**	**0.04**

*Includes "Shrubland", "Herbaceous" and "Pasture / Hay"

Figure 5 illustrates the general area in which Natural Grassland was converted to sorghum between 2008 and 2022. Each cell represents the proportion of area on 6 km grids (approximately 3,600 hectares). **Almost all** of the colored areas had **less than 10% conversion** from 2008 through 2022.

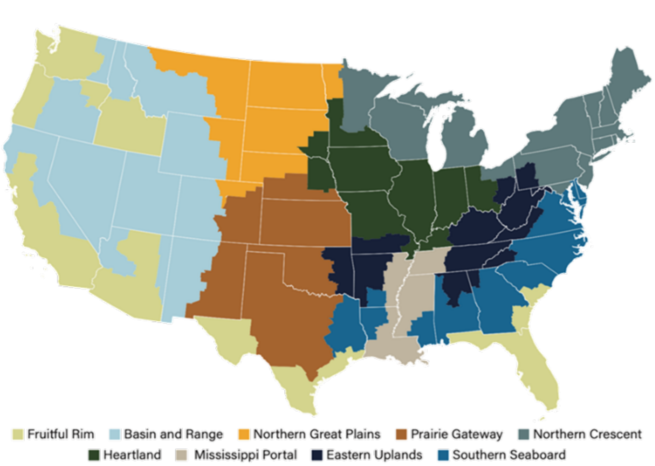
Figure 5. Conversion of Natural Grassland to Cropland with Sorghum Footprint (2008 - 2022)

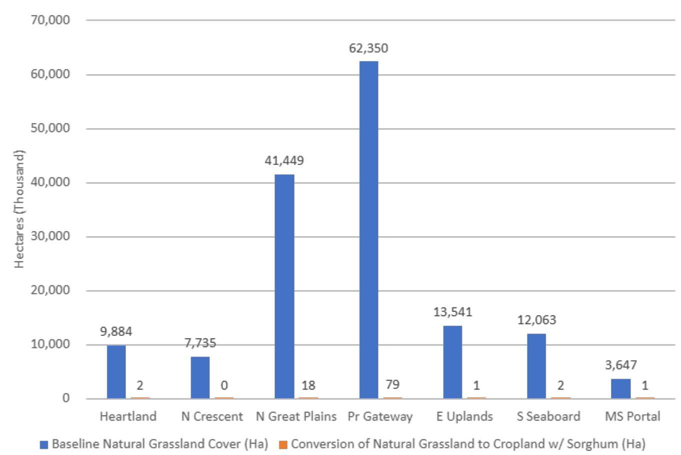


Source:GeoMARC Geospatial-based LCLU Mapping with ANLCD and CDL Data.

Figure 6 further illustrates the negligible proportion of total Natural Grassland that was converted to sorghum from 2008 through 2022 by FRR.

Figure 6. Natural Grassland Baseline and Conversion to Cropland with Sorghum Footprint





NOTE: The Fruitful Rim, and Basin and Range FRRs are omitted from the bar chart due to negible conversion of Natural Grassland to Cropland with Sorghum Footprint.

Source: USDA, Economic Research Service farm resource regions.

3. SUB-NATIONAL / SECTORAL RISK ASSESSMENT FOR LEGAL DEFORESTATION AND CONVERSION

3.1. ASC DUE DILGENCE PATHWAY: INDUSTRY / SECTORAL ASSESSMENT

The risk assessment conducted in this report responds to the required DD process developed by ASC. Figure 7 summarizes the four DD pathways ASC created to help feed manufacturers determine the risk level for ingredient sourcing risk factors such as risk of legal deforestation / conversion. If a country of origin is deemed to be either 'medium-risk' or 'high-risk' for a specific risk factor, additional DD is required. This additional DD is to determine if the country of origin can be identified as 'low-risk', and, therefore, meet the ASC Feed Standard requirements for that risk factor.

Figure 7. ASC Due Diligence Pathways

1	2	3	4
Country Risk Score Card	**Industry / Sector / Fishery Assessment**	**Ingredient Manufacturer Assessment**	**Certification**
Developed by ASC Based on publicly available indices Traffic light system to rank each country into low / medium / high risk	Assessment conducted by competent persons (feed mill / external) Traceability level depends on risk outcome E.g. Review published reports, collect data from buyers or technical staff (cf. guidance)	Assessment conducted by competent persons (feed mill / external) Similar to an internal audit of suppliers Ingredient Manufacturer must provide evidence to mill	List of ASC approved 3rd party schemes Criteria developed by ASC (standard setting process, assurance, traceability & standard content)

Source: ASC Feed Standard Principle 2 & 5 Due Diligence Deep Dive Webinar

ASC designated U.S.-originated plant ingredients as 'medium- risk' for legal deforestation / conversion using the "Country Risk Score Card" pathway. This designation, therefore, triggers the need for the feed mills sourcing plant-based ingredients from the United States to demonstrate 'low-risk' for each feed ingredient such as sorghum-derived feed products.

To help feed mills sourcing U.S.-originated sorghum-based aquaculture feed ingredients, the "Industry/Sector/Fishery Assessment" DD pathway can be used to demonstrate the risk level of legal deforestation / conversion as part of the ASC Feed Ingredient Certification[11]. ASC's guidance states that the sub-national / sectoral assessment is to be conducted in a successive manner. This approach is based on three levels of traceability, beginning with a high-level analysis (Level 1 of traceability – for example a region) and moves to more granular assessments when warranted based on the initial

[11] ASC Feed Interpretation Manual V1.1 (1 May 2025), beginning on page 180.

findings, such as if 'low-risk' cannot be determined at a broader scale. Level 2 of traceability consists of groups of production units located in close geographic proximity and under common management, and Level 3 of traceability is defined as productions units such as farms.

The ASC offers no specific guidance on how to conduct a sub-national / sectoral assessment. Therefore, an adaptation of ASC's Country Risk Score Card is used for the present risk assessment. ASC's Country Risk Card methodology[12] uses three components to designate a country's risk level for legal deforestation / conversion:

1. A list of **indicators** for plant-based primary raw material for legal deforestation / conversion risk,
2. **Risk thresholds** for the indicators, and
3. **Weights** for each indicator to calculate the weighted-average score to determine the overall risk level.

The second (risk indicator thresholds) and third (risk indicator weights) components of ASC's Country Risk Score Card methodology for plant-based primary raw material legal deforestation / conversion risk are summarized in Figure 8. ASC acknowledges that there is no international agreed classification for high deforestation. Therefore, it uses Brazil's definition of high forest loss because of the global consensus of the seriousness of deforestation in Brazil. ASC's permanent agricultural-driven deforestation risk thresholds are based on expert opinion (AS-INF-012, page 32). ASC does not provide any explanation for its selection of the risk indicator weights.

Figure 8. Overview of ASC's Indicator Risk Thresholds for Plant-Based Primary Raw Material Environmental (Legal D/C) Risk and Weights

	Threshold			
Deforestation	**LOW**	**MEDIUM**	**HIGH**	**Weight**
5.1: Risk due to high forest cover	0-19.9%	20.0-29.9%	≥ 3.0%	10%
5.2: Overall risk of forest loss in natural forest	0-1.9%	2.0-2.99%	≥ 3.0%	10%
5.3: Permanent agricultural-driven deforestation risk	0-9.9%	10.0-14.9%	≥ 15%	40%
5.4: Identified in WWF Deforestation Fronts 2021			YES	20%
	Threshold			
Conversion	**LOW**	**MEDIUM**	**HIGH**	**Weight**
5.5: Identified in WWF Plow Print 2024			YES	20%

Source: ASC Feed Standard Country Score Cards Methodology and Rationale, Version 2.0 – Issue Date: June 2025

[12]ASC Feed Standard Country Score Cards Methodology and Rationale, V 2.0, June 2025 (ASC-INF-012)

3.2. RISK ASSESSMENT METHODOLOGY

A rigorous sub-national / sectoral risk assessment for legal deforestation / conversion is developed for this risk assessment by leveraging the unique and accurate georeferenced assessment of both natural forest and natural grassland conversion to cropland and into sorghum specifically. This risk assessment, therefore, consists of indicators reflecting actual evidence of deforestation / conversion levels in the United States, not estimates or binary indicators that do not accurately assess U.S. deforestation / conversion.

Six robust and timely indicators of risk are defined for the sub-national / sectoral risk assessment (Table 4). Three of the indicators assess risk associated with legal deforestation (Indicators F1, F2, and F3 (S)) while the remaining indicators reflect risk associated with grassland conversion (G1, G2 and G3 (S)).

Table 4. Risk Indicators Descriptions

Indicator ID	Indicators	Description	Risk
F1	Baseline Natural Forest Cover (1985 -2007)	The proportion of landmass that was covered in Natural Forest as of the baseline year.	The higher the proportion, the greater the risk of future deforestation. (Prospective)
F2	Gross conversion of Natural Forest to Cropland (2008 -2022)	The percentage of gross Natural Forest that was converted to Cropland.	The higher the percentage, the greater the commodity-driven deforestation. (Retrospective)
F3 (S)	Gross Natural Forest expansion to Cropland with sorghum footprint (2008 – 2022)	The percentage of Natural Forest that was converted to Cropland with a sorghum footprint. (Gross conversion)	The higher the percentage, the greater the sorghum-specific driven deforestation. (Retrospective)
G1	Baseline Natural Grassland Cover (1985 - 2007)	The proportion of landmass that was covered in Natural Grassland as of the baseline year.	The higher the proportion, the greater the risk of future grassland conversion. (Prospective)
G2	Gross conversion of Natural Grassland to Cropland (2008 – 2022)	The percentage of gross Natural Grassland that was converted to Cropland.	The higher the percentage, the greater the commodity-driven grassland conversion. (Retrospective)
G3 (S)	Gross Natural Grassland expansion to Cropland with a sorghum footprint (2008 – 2022)	The percentage of Natural Grassland that was converted to Cropland with a sorghum footprint. (Gross conversion)	The higher the percentage, the greater the sorghum-specific driven grassland conversion. (Retrospective)

The six risk indicators for legal deforestation / conversion, along with the thresholds and weights used for the analysis, are shown in Figure 9. The explanations for the indicator thresholds and weights are as follows:

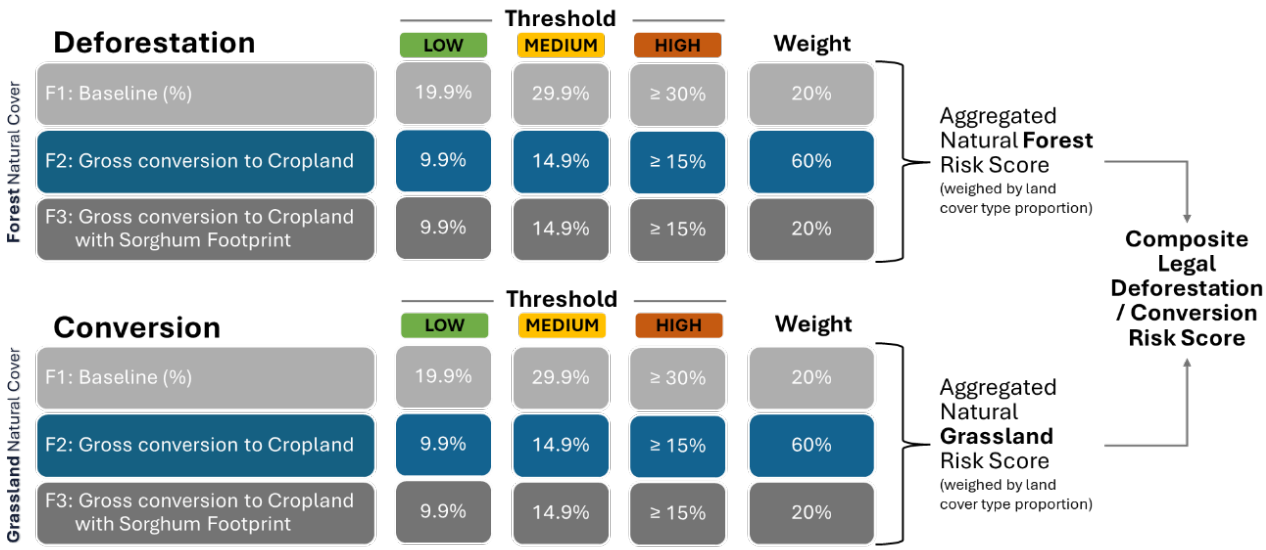
- **Risk Indicator Thresholds**:
  - *Baseline*: Same thresholds as ASC's Country Risk Score Card Methodology for "Risk due to High Forest Cover"
  - *Gross Conversion to Cropland*: Same thresholds as ASC's Country Risk Score Card Methodology for "Permanent Agricultural-driven Deforestation Risk"

  - *Gross Conversion to Cropland with Sorghum Footprint*: Same thresholds as ASC's Country Risk Score Card Methodology for "Permanent Agricultural-driven Deforestation Risk"

- **Aggregate Risk Score Weights**:
  - Two aggregated natural risk scores are calculated, one for Natural Forest and one for Natural Grassland.
  - For each aggregate score, internal expert judgement is used, guided by ASC's weights of 10% for forest cover and 40% for conversion to permanent agriculture. Higher weights (20% and 60%) are applied in this analysis, respectively, to both natural forest and grassland cover and conversion to permanent agriculture (cropland) than used by ASC.

- **Composite Score Weights**:
  - Unlike the ASC Country Risk Score Card methodology, a composite score is calculated using the Aggregated Natural Forest and Natural Grassland Risk Scores. This approach is possible due to having sufficient information to use three indicators for each type of risk (deforestation and (grassland) conversion). For example, unlike the ASC Country Risk Score Card methodology having a binary value representing conversion risk (whether the country is identified in the WWF Plow Print report), this analysis has actual data on baseline Natural Grassland and conversion of Natural Grassland to cropland and specifically to sorghum.
  - The Aggregated Natural Forest and Natural Grassland Risk Scores are weighted by the proportion of baseline natural forest and natural grassland on the land area represented in the calculation. For example, at the national level, the proportion of natural forest and natural grassland combined that is natural forest is 37% and the proportion of natural grassland is 63%; therefore, the Aggregate Natural Forest Risk Score and the Aggregate Natural Grassland Risk Score are weighted by 37% and 63%, respectively, to derive the composite legal deforestation / conversion risk score. This approach rigorously reflects the natural area, forest or grassland, at risk at the geographic level which is being assessed.

Figure 9. U.S. Risk Indicators' Thresholds and Weights



REPORTING OF RISK ASSESSMENT RESULTS

To meet ASC's criterion of conducting and reporting the risk assessment results on a sub-national or sector level for this pathway, the risk assessment is calculated and reported at the Farm Resource Region (FRR) level (Figure 4), in addition at the U.S. national level (for comparison to ASC's Country Risk Score Card designation).

3.3. U.S. RESULTS: RISK ASSESSMENT

> *Conclusion: Following the ASC risk assessment framework for legal deforestation / conversion, the individual aggregate risk scores for forest and grassland conversion in the United States are estimated as 'low-risk'. This designation applies to the national level, as well as the sub-regional levels (FRRs) developed in the assessment. The Composite Legal Deforestation and Conversion Risk Score for all FRRs and at the U.S. national level is 'low-risk', therefore, indicating that sorghum-derived aquaculture feed ingredients sourced from the United States are at 'low risk' for legal deforestation / conversion.*

The assessment for plant-based primary raw material legal deforestation / conversion risk at the national level is reported in Figure 10. The national Baseline Natural Forest Cover is 24.5% and Baseline Natural Grassland Cover is 41.5%, therefore, classifying their Baseline Natural Cover risk as 'medium-risk' and 'high-risk', respectively (i.e. indicating the significant presence of each cover type within the contiguous United States). However, the United States is designated as 'low-risk' for Gross Conversion of Natural Forest and Gross Conversion of Natural Grassland to cropland, in general, and to sorghum, specifically. These designations generate 'low-risk' Aggregated Risk scores for

Natural Forest Cover and Natural Grassland Cover and a ‘low-risk’ Composite Legal Deforestation / Conversion Risk Score at the U.S. national level.

Figure 10. National Risk Assessment for Legal Deforestation / Conversion

Category	Baseline Natural Cover	Gross Conversion of Natural Cover to Cropland	Gross Conversion of Natural Cover to Cropland w/ Sorghum Footprint	Aggregated Risk Score	Composite Legal Deforestation / Conversion Risk Score
Forest Natural Cover	Medium	Low	Low	Low	Low
Grassland Natural Cover	High	Low	Low	Low	

The Farm Resource Region (FRR) level assessment for plant-based primary raw material legal deforestation / conversion risk is reported in Figure 11.

Figure 11. Farm Resource Region Risk Assessment for Legal Deforestation / Conversion

	Forest Natural Cover				Grassland Natural Cover				
Farm Resource Region	Baseline Natural Cover	Gross Conversion of Natural Cover to Cropland	Gross Conversion of Natural Cover to Cropland w/ Sorghum Footprint	Aggregated Risk Score	Baseline Natural Cover	Gross Conversion of Natural Cover to Cropland	Gross Conversion of Natural Cover to Cropland w/ Sorghum Footprint	Aggregated Risk Score	Composite Legal Deforestation / Conversion Risk Score
Heartland	Low	Low	Low	Low	Low	Low	Low	Low	Low
Northern Crescent	High	Low	Low	Low	Low	Low	Low	Low	Low
Northern Great Plains	Low	Low	Low	Low	High	Low	Low	Low	Low
Prairie Gateway	Low	Low	Low	Low	High	Low	Low	Low	Low
Eastern Uplands	High	Low	Low	Low	Medium	Low	Low	Low	Low
Southern Seaboard	High	Low	Low	Low	Low	Low	Low	Low	Low
Fruitful Rim	Low	Low	Low	Low	High	Low	Low	Low	Low
Basin and Range	Medium	Low	Low	Low	High	Low	Low	Low	Low
Mississippi Portal	Medium	Low	Low	Low	Low	Low	Low	Low	Low

Three FRRs (Northern Crescent, Eastern Uplands and Southern Seaboard) are classified as ‘high-risk’ for Baseline Natural Forest Cover (i.e. high presence of forest cover). Sorghum is not predominately grown in these FRRs.

Four FRRs (Northern Great Plains, Prairie Gateway, Fruitful Rim, and Basin and Range) are classified as ‘high-risk’ for Baseline Natural Grassland Cover (i.e. high presence of grassland cover). The Basin and Range FRR is not a significant area for U.S. sorghum production.

While there is a sub-set of the FRRs designated as ‘high-risk’ and ‘medium-risk’ for Baseline Natural Forest and Natural Grassland Cover, all nine FRRs are designated ‘low-risk’ for Gross Conversion of Natural Cover to cropland, in general, and to sorghum, specifically. This results in ‘low-risk’ Aggregate Risk Scores for both Natural Forest Cover and Natural Grassland Cover and a ‘low-risk’ Composite Legal Deforestation / Conversion Risk Score for all nine FRRs.

This additional DD, at the sub-national and at the U.S. national levels, provides sufficient evidence that sorghum-derived aquaculture feed ingredients sourced from the United States comply with ASC's Feed Ingredient Standard certification requirement of 'low-risk' for legal deforestation / conversion.

4. DEFORESTATION / CONVERSION MONITORING AND UPDATES

Conversion of natural forests and natural grassland is an ongoing phenomenon that requires continued monitoring. The geospatial data used for this analysis are from two annual data sources - the ANLCD and the CDL. These annual products provide the opportunity for annual collection of data from the products. However, given the trajectory-approach analysis of 5-year windows for the Change Detection Layer, the next update of the Change Detection Layer will only occur when USGS and USDA/NASS make data through 2027 available. This will permit a compilation of an updated Change Detection Layer consistent with the data layer constructed for this assessment and an updated risk assessment of legal deforestation / conversion.

5. CLOSING REMARKS

Public and private stakeholders are addressing concerns about deforestation and land conversion on key ecosystems and the climate by developing standards and requirements for demonstrating low rates of legal deforestation / conversion.

The United Sorghum Checkoff Program, as a key stakeholder representing the U.S. sorghum industry internationally, recognizes the importance of the deforestation / conversion issue and therefore, has taken proactive action by releasing this report.

The characterization of land cover and land use performed for this work has created new and unique Baseline and Change Detection Data Layers that show of low rates of deforestation and grassland conversion in the United States.

The geospatial mapping results presented in this report inform the risk assessment of legal deforestation / conversion required by ASC's Feed Ingredient Standard. The risk assessment concludes that the United States is at 'low-risk' for legal deforestation / conversion at sub-national and national levels.

This analysis generates robust and scientifically-based evidence of deforestation / conversion trends, which form the foundation of the risk assessment; however, deforestation and grassland conversion is not static. The threats to key ecosystems and the climate are ongoing and require continued monitoring and measurement to ensure that the reliance on plant-based ingredients is not at the detriment to the ecosystems everyone strives to preserve.

The United Sorghum Checkoff Program, on behalf of its stakeholders, is committed to ongoing and transparent monitoring and measurement of natural forest and grassland conversion to cropland, in general, and to sorghum, specifically, to validate the continued low rate of deforestation and grassland in the United States.

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ABBREVIATIONS

ANLCD	Annual National Land Cover Data
ASC	Aquaculture Stewardship Council
CDL	Cropland Data Layer
DCF	Deforestation and Conversion-free
DD	Due Diligence
FRR	Farm Resource Regions
LCLU	Land cover and land use
LCLUC	Land cover and land use change

GLOSSARY

Logical Refinement	An advanced filtering phase that applies explicit temporal logic to pixel histories; for example, allowing for intermittent or rotational ag presence to confirm expansion or a strict ag→non-ag sequence to confirm abandonment. Logical refinement reduces false positives and enforces chronological consistency.
Minimum Mapping Unit (MMU)	The smallest areal extent considered valid for mapping or analysis. In this project, the MMU was set to 5 acres (~23 pixels), ensuring all mapped change features are large enough to represent real landscape patterns rather than classification noise.
Natural Forests	Land with forest cover that possess many or most of the characteristics of a forest native to the given site, including species composition, structure and ecological function; includes primary forests, regenerated forests, managed natural forests and degraded forests, which during the 1985 – 2007 timeframe had no cultivated agricultural activity.
Natural Grasslands	Herbaceous, shrubs, and pasture/hay land cover that possess many or most of the characteristics of grasslands native to the given site, including species composition, structure and ecological function. This includes primary grasslands, regenerated grasslands, managed natural grasslands and degraded grasslands, which during the 1985 – 2007 timeframe had no cultivated agricultural activity.
Non- natural Forests	Land with forest cover that at any time during the 1985 – 2007 timeframe showed cultivated agricultural activity.
Non- natural Grasslands	Land with grassland cover (herbaceous, shrubs, and pasture/hay) that at any time during the 1985 – 2007 showed cultivated agricultural activity.
Pixel	A fundamental element comprising a digital image derived from satellites or remote sensing.
Spatial Filtering	A post-processing operation that smooths or regularizes raster data by examining pixel neighborhoods through kernels. Spatial filtering removes isolated misclassifications and enhances contiguous patterns, improving map readability and thematic accuracy.
Spectral Profile	A plot of pixel values (reflectance / intensity) against specific wavelengths (e.g., red, green, blue, infrared) for a selected area on an image.
Temporal Profile	A series of satellite imagery of the same pixel over time.

APPENDIX — GEOSPATIAL-BASED LAND COVER / LAND USE MAPPING METHODOLOGY

OVERVIEW

The mapping and characterizing of land cover change with the U.S. Geological Survey's (USGS) Annual Land Cover Database (ANLCD) in the United States from 1985-2022 is designed to quantify and characterize agricultural land change across the contiguous United States (CONUS) between 1985 and 2022. The workflow integrates ANLCD and U.S. Department of Agriculture's Cropland Data Layer (CDL) datasets to identify stable land cover conditions, agricultural expansion[13] (or conversion) and agricultural abandonment[14]. The analysis follows a structured multi-stage framework encompassing base layer development, change detection, post-processing, validation, and final classification refinement.

BASE LAYER CONSTRUCTION (1985–2007)

The foundational baseline for all analyses is developed using ANLCD data spanning 1985 to 2007. Each ANLCD year is recoded into a binary representation of agriculture (1) versus non-agriculture (0). To capture longer-term patterns, individual years are grouped into sequential multi-year windows: one 3-year window (1985–1987) and four 5-year windows (1988–1992, 1993–1997, 1998–2002, and 2003–2007).

Each pixel is assigned a composite code that preserves both its dominant background class and agricultural lineage. This composite base layer establishes the long-term agricultural and non-agricultural context against which all subsequent change is measured.

CHANGE DETECTION AND LAYER DEVELOPMENT (2008–2022)

Agricultural change is identified using ANLDC annual rasters from 2008 through 2022. The study divides this timeframe into three 5-year windows to detect the timing and persistence of transitions:

- **W1:** 2008–2012
- **W2:** 2013–2017
- **W3:** 2018–2022

[13] This technical description uses the term "expansion" interchangeably with "conversion".
[14] While this study does not include cropland abandonment in the risk assessment component, the identification of agricultural abandonment, as part of complicated land cover / land use dynamics, is a natural outcome of the geospatial-based assessment yet overlooked. It is, therefore, described throughout this appendix but is not included in the plant-based raw material risk assessment for legal deforestation / conversion since abandonment is not the focus of this study. However, the exclusion of abandonment from the analysis presented in this report does not impact the results in any way.

For each window, change is classified as:

Expansion — where a base non-ag pixel converts to agriculture in a later window.

Abandonment — where a base agricultural pixel reverts to sustained non-ag.

Each change event receives a unique code indicating both direction (expansion or abandonment) and timing (W1 expansion, W2 expansion, or W3 expansion). These change layers form the temporal backbone of the analysis. All expansion pixels are also assigned an ag lineage designator for robust understanding of the impact that prior agricultural production had on expansion pixels.

REFINEMENT AND TEMPORAL ALIGNMENT

Initial change detection is followed by a refinement phase that applies logical filters to minimize noise and distinguish between transient and sustained transitions. Two parameter sets are used:

- **Expansion Refinement** assesses less dominant change areas for better understanding of their trajectory. This refinement adds approximately 880,000 acres (≈ 356 thousand hectares) (≈ 5% of total expansion area) to the pool of identified expansion pixels.
- **Abandonment Refinement** requires a strict temporal sequence for abandonment to be validated (that is, once abandonment is identified, those pixels can never display an agricultural signature again). This process removes approximately 590,000 acres (≈ 239 thousand hectares) (≈ 5% of total abandonment area) that do not meet the strict trajectory criteria.

A subsequent temporal alignment phase applies a logical check to ensure that change is assigned to the correct 5-year window. If change is detected in the window preceding its initial identification, the pixels are re-assigned accordingly (for both expansion and abandonment).

SPATIAL FILTERING

Spatial post-processing reduces pixel-level noise and enforces local coherence. Several kernels are evaluated—including full 3×3, plus-shaped, and corridor filters—to assess their ability to remove isolated misclassifications without eroding narrow agricultural features. The full 3×3 filter is ultimately selected as optimal, preserving larger homogeneous clusters while eliminating linear agricultural offshoots and small speckle clusters that failed to form cohesive patterns.

MINIMUM MAPPING UNIT (MMU) ENFORCEMENT

A minimum mapping unit (MMU) filter ensures that only spatially coherent clusters of change are retained. Using connected-component labeling with 4-neighbor connectivity, all clumps of target change pixels are identified. Those smaller than the MMU threshold (5 acres or about 2 hectares, ≈23 pixels) are dissolved into a non-ag class if originally labeled expansion, or into an ag class if originally labeled abandonment. This eliminates small, noise-driven features and aligns the final maps with standard cartographic generalization principles.

CONFIDENCE DIAGNOSTICS

To evaluate classification reliability, each pixel is linked to the ANLCD confidence layer corresponding to its agricultural or non-agricultural years. Median confidence and interquartile ranges (IQR) are computed for all years when a pixel is agricultural.

- **1985–2007 (all ag pixels ≥3× ag):** Median = 82%; IQR = 62–91; 68% ≥70% confidence, 55% ≥80% confidence
- **2008–2022 (all ag pixels ≥3× ag):** Median = 84%; IQR = 69–91; 75% ≥70% confidence, 60% ≥80% confidence

Both expansion and abandonment pixels consistently exhibit lower median confidence than stable agriculture, validating that detected transitions correspond to areas of legitimate uncertainty rather than random noise:

- **Expansion (2008–2022, ag pixels ≥3× ag):** Median = 60%; IQR = 48–74; 34% ≥70% confidence, 14% ≥80% confidence
- **Abandonment (2008–2022, ag pixels ≥3× ag):** Median = 57%; IQR = 46–67; 21% ≥70% confidence, 8% ≥80% confidence

These confidence results guide a subsequent cross-dataset validation to confirm that uncertainty patterns align with actual agreement between NLCD and CDL.

CROSS-DATASET VALIDATION

Given the reduced confidence of ag pixels undergoing change, a secondary diagnostic assesses the overlap and agreement of change identified in **NLCD** and **CDL** from 2008–2022. This validation focuses on (a) agreement between NLCD and CDL and (b) disagreement where change was detected in NLCD only (CDL-only change was outside the study scope).

Results showed that 89% of expansion and 80% of abandonment change pixels are temporally and thematically consistent across datasets, supporting the robustness of the change detection framework.

ASSIGNING NON-AG CLASSES TO ABANDONMENT AND CROP TYPE (CORN/SORGHUM) TO EXPANSION

To provide ecological context for agricultural loss, abandonment pixels are reclassified by their post-agricultural ANLCD category. Each is assigned to a dominant non-ag land-cover type (e.g., forest, grass/herbaceous, wetland, or urban). The resulting layers distinguish between **ecological abandonment** (e.g., ag → forest or grassland) and **developmental abandonment** (e.g., ag → urban).

The CDL (2008–2022) is also used to assign crop identity to expansion pixels. Any expansion pixel with at least one year of sorghum presence is classified accordingly. In addition to binary identification, the frequency of plantings is retained to capture crop-specific intensity across time windows.

EXPANSION SUMMARIES

Expansion results are summarized across multiple spatial scales, including Farm Resource Region (FRR), state, and 6×6 km and 3×3 km grid levels. Reported aggregated tables include:

- Total and proportional gross expansion by window (W1–W3), with ag lineage
- Breakdown by dominant background class (e.g., grass/herbaceous vs forest origins)
- Crop-specific drivers (sorghum)

These outputs enable flexible spatial and temporal comparisons of agricultural frontier activity.

ABANDONMENT SUMMARIES

An equivalent analytical framework is applied to abandonment layers, summarizing the timing, magnitude, and destination class of former agricultural pixels. Former ag areas are categorized by the timing of transition and their new dominant non-ag type. These summaries provide a mirror perspective to expansion, allowing direct comparison of gains and losses in agricultural areas and highlighting regions of contraction.

MAPPING

Uniform 6×6 km and 3×3 km grids are overlaid across CONUS to facilitate consistent spatial aggregation. For each grid cell, total acreage and percent share of expansion and abandonment are computed for each time window. This framework supports cartographic visualization and higher-order modeling of spatial patterns at standardized resolutions.

OVERALL WORKFLOW SUMMARY

In sequence, the methodology proceeds as follows:

1. Construct a stable agricultural baseline (1985–2007) from ANLCD.
2. Detect directional agricultural change (2008–2022) using ANLCD and CDL, with crop specifics derived from CDL.
3. Refine results using logical refinement, temporal alignment, spatial filtering, and MMU enforcement.
4. Validate transitions via confidence and cross-dataset analyses.
5. Summarize expansion and abandonment patterns across spatial and temporal scales.
6. Contextualize abandonment outcomes with ecological or developmental end states and crop-specific influence on expansion.

This structured, multi-stage workflow produces a rigorously filtered, confidence-weighted, and ecologically interpretable set of change layers that form the empirical foundation for long-term agricultural trajectory analysis across the United States.

All spatial analyses are conducted in Python (rasterio, NumPy, SciPy, pandas) and ArcGIS Pro using 30 m resolution data.

TECHNICAL GLOSSARY

Agricultural Lineage	A pixel-based history of agricultural presence derived from sequential land cover classifications. It records how often and in which periods a location was agricultural, providing a measure of its "agricultural memory." Lineage codes were established to indicate increasing recurrence of agricultural presence across earlier windows (1985–2007).
Base Layer	The foundational raster representing stable agricultural and non-agricultural conditions prior to the change-detection period. Built from NLCD (1985–2007), it encodes each pixel's dominant background land cover and any existing agricultural lineage, serving as the reference state for detecting expansion or abandonment.
Confidence Layer	A companion raster indicating the reliability of each pixel's classification, expressed as a percentage confidence (0–100). NLCD confidence layers quantify the probability that a pixel's label (classification) is correct. These values are used to assess and validate detected changes.
Connected-component Labeling	A computational method for identifying contiguous groups ("clumps") of pixels that share the same value or class. Using 4- or 8-neighbor connectivity, it labels each distinct cluster, allowing measurement of size and shape – essential for applying a minimum mapping unit threshold.
Corridor Filters	Directional kernels emphasizing linear or elongated patterns, often used to preserve narrow agricultural or riparian features while smoothing noise in adjacent pixels. Tested alongside 3×3 and plus-shaped kernels to determine the best spatial filtering structure.
Georeference	The spatial referencing system that defines a raster's position on the Earth's surface. It includes coordinate system, projection, cell size, and geographic extent. Georeferencing ensures all input and output rasters align precisely for pixel-to-pixel comparison and temporal stacking.
Kernels	Small, moving window templates (e.g., 3×3 pixels) used in spatial filtering to evaluate or modify pixel values based on their neighborhood. Each kernel defines the shape and size of the area influencing a pixel's outcome – such as a full 3×3 square, plus-shaped, or elongated corridor.
Local Coherence	The degree to which neighboring pixels share similar classifications or change states. High local coherence indicates spatially contiguous, meaningful patterns rather than isolated noise. Post-processing steps such as spatial filtering and MMU enforcement are designed to strengthen local coherence.

Logical Filters	Rule-based operations that evaluate pixel trajectories through time to identify implausible or inconsistent patterns (e.g., a single-year anomaly between long runs of stability or stable pattern after change detection). Logical filters ensure that only temporally consistent sequences are retained as genuine change.
Logical Refinement	An advanced filtering phase that applies explicit temporal logic to pixel histories; for example, allowing for intermittent or rotational ag presence to confirm expansion or a strict ag→non-ag sequence to confirm abandonment. Logical refinement reduces false positives and enforces chronological consistency.
Minimum Mapping Unit (MMU)	The smallest areal extent considered valid for mapping or analysis. In this project, the MMU was set to 5 acres (~23 pixels), ensuring all mapped change features are large enough to represent real landscape patterns rather than classification noise.
MMU Enforcement	The process of applying the MMU threshold to connected-component results. All pixel clusters smaller than the specified MMU (5 acres) are dissolved into the surrounding dominant class (non-ag for expansion, ag for abandonment). This step enforces spatial generalization standards.
Post-processing	All procedures applied after initial classification or change detection to improve map quality and consistency. Examples include logical refinement, spatial filtering, MMU enforcement, and temporal alignment (see definitions below). Post-processing converts raw change signals into cartographically and analytically reliable layers.
Raster	A gridded spatial dataset composed of equally sized cells (pixels), where each pixel stores a numerical value representing a land cover class, probability, or continuous measurement. In this project, rasters are 30 m × 30 m grids aligned across CONUS, enabling pixel-level comparison through time of different land cover types.
Spatial Scale	The geographic resolution or extent at which patterns, processes, or changes are analyzed. In this project, spatial scale can operate at multiple levels – from 30-m pixels to 3×3 km and 6×6 km grid cells, to county, state, and farm resource regions. Different spatial scales reveal different patterns: pixel-level detail shows fine-grained land conversion, while coarser scales highlight regional trends and aggregate dynamics.
Spatial Filtering	A post-processing operation that smooths or regularizes raster data by examining pixel neighborhoods through kernels. Spatial filtering removes isolated misclassifications and enhances contiguous patterns, improving map readability and thematic accuracy.

Temporal Alignment	A correction step ensuring that detected change events are assigned to the correct time window. If a transition appears mis-timed (e.g., detected in W2 but actually occurred in W1), temporal alignment shifts it to the appropriate 5-year period to maintain chronological accuracy.
Temporal Scale	The length, frequency, and structure of time intervals used to assess change. Here, temporal scale involves both annual data (NLCD/CDL) and multi-year windows (e.g., 1985–1987, 1988–1992, 1993-1997, 1998-2002, 2003-2007, and W1–W3 from 2008–2022). Temporal scale determines the sensitivity to short-term variation versus long-term trends, enabling detection of sustained expansion or abandonment rather than year-to-year noise.
Trajectory-based Analysis	An analytical approach that examines the full sequence of land cover statuses a pixel can experience over time, rather than assessing isolated year-to-year transitions. In this project, trajectory-based analysis tracks each pixel's time-ordered land cover history (e.g., ag → non-ag, stable grassland → expansion → stable ag, or grassland w/ag lineage → expansion → rotational ag) and uses that temporal narrative to classify outcomes such as expansion (w/ or w/o ag lineage), abandonment, or long-term stability (i.e., no change). This method captures direction, timing, persistence, and lineage, providing a richer understanding of landscape change than traditional two-date (start date and end date) comparisons.

BIOGRAPHIES / QUALIFICATIONS

SUMMARY TABLE OF QUALIFICATIONS

	Deforestation / Conversion Risk Assessment	Geospatial Assessment	Geospatial Assessment
	Sharon Bard	Joshua Pritsolas	Randall Pearson
Education	Ph.D., Agricultural Economics	M.S., Geography	Ph.D., Geography (Remote Sensing, Hydrologic Modeling and Physical Landscapes)
Work Experience	Over 25 years experience in the agriculture sector, including risk assessment and land cover / use assessment	Over 10 years experience with Remote sensing and Image Processing	Over 30 years experience with Remote sensing and Image Processing
ASC Feed Standard Training	Not available at time of risk assessment (12/15/2025)	N/A	N/A
Geospatial-based LCLU Mapping	Oversight / Guidance	Lead	Lead
ASC Risk Assessment	Lead	Oversight / Guidance	Oversight / Guidance

TERRA ECONOMICS / SHARON K. BARD

Dr. Sharon Bard is principal and founder of Terra Economics which specializes in agricultural sustainability, including quantification of environmental outcomes, reporting and standards; land cover / land use; biofuels production and policy; grain quality; and economic analysis of agricultural supply chains (supply, demand, and trade). Bard has worked on projects spanning the agricultural industry from agricultural producers to food retail businesses and utilizes numerous qualitative and quantitative methodologies in conducting her research. Bard has managed numerous multi-disciplinary project teams and delivered written reports and presentations of project results on behalf of the project teams to clients. Prior to founding Terra Economics, Bard was an agricultural economic consultant and project manager with Centrec Consulting Group for over 20 years. A representative sampling of Bard's work includes:

- Monitor U.S. land cover and land use for Clean Fuels Alliance America (ongoing).
- Currently evaluating and developing recommendations for risk-based approaches as alternatives to a quantified approach to measuring indirect or induced land use change on behalf of Clean Fuels Alliance America (ongoing).
- Contribute to an ongoing effort for monitoring relevant sustainability-related standards and guidance for agriculture and biofuels on behalf of Clean Fuels Alliance America.
- Participated in United Soybean Board's Land Use Change Initiative.

- Reviewed sustainability reporting and guidance and developed recommendations for relevant guidance and reporting for the soybean industry.
- Worked with a team of geospatial scientists to develop a land cover/use dataset. This project included identifying the appropriate nomenclature and imagery to use and developing the algorithms and training to classify the images.
- Researched nomenclature issues and developed recommendations for more consistent use of land cover and land use nomenclature.
- Conducted the research and prepared a report and responses for addressing land cover / use issues in the EPA's "Biofuels and the Environment: Second Triennial Report to Congress" and the EPA's "Biofuels and the Environment: Third Triennial Report to Congress" on behalf of the National Biodiesel Board / Clean Fuels Alliance America.
- Developed risk assessment training modules for the agricultural lending industry.
- Developed a method for assessing risk attitudes of farmers on behalf of USDA Economic Research Service; research findings were published in "Developing a scale for assessing risk attitudes of agricultural decision makers", International Food and Agribusiness Management Review 3 (2000) 9-25, and "Assessing Farmers' Attitudes toward Risk Using the' Closing-in' Method", Journal of Agricultural and Resource Economics,(2001) 26(1): 248-260.

Bard received a B.S. in Animal Science and an M.S. and a Ph.D. in Agricultural Economics from the University of Illinois. Bard also has experience in production agriculture as she was raised on a ranch in Arizona and currently lives on a cash grain farm in east-central Illinois.

GEOMARC

GEOMARC / RANDALL S. PEARSON, PH.D.

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Southern Illinois University Edwardsville (SIUE)
420 University Park Drive, Edwardsville, IL 62025
Phone: 618-650-2278
Email: rapears@siue.edu

EARNED DEGREES

Institution	Area	Degree	Year Awarded
Murray State University	Geology (Landforms, Soils, Hydrology)	B.S.	1984
Murray State University	Geoscience (Remote Sensing)	M.S.	1986
Indiana State University	Geography (Remote Sensing, Hydrologic Modeling and Physical Landscapes)	Ph.D.	1994

EMPLOYMENT HISTORY

Years	Position
2021 – Present	Director, GeoSpatial Mapping, Applications, and Research Center (GeoMARC), Graduate School – SIUE
1996 – 2021	Director, Laboratory for Applied Spatial Analysis (LASA), College of Arts and Sciences - SIUE
1995 – Present	Professor, Associate Professor, Assistant Professor, Dept. of Geography, SIUE
1993 – 1995	Director, Center for Applied Spatial Analysis, Tacoma, WA
1988 – 1993	Senior Scientist (Environmental and Agricultural Program Manager), NASA – Space Remote Sensing Center, Stennis Space Center, MS

RESEARCH INTERESTS

Remote sensing and Image Processing – Advanced Image Classifiers using Machine Learning – Deep Learning Algorithms – Quantification of Land Cover Variables – Computer Modeling

SYNERGISTIC ACTIVITIES

1. I am the Director of the GeoSpatial Mapping, Research, and Applications Center which has 8 full time employees and is fully funded through external grants and contracts. GeoMARC, which I formed in 1996, has flourished as one of SIUE's primary research facilities over the past decade. GeoMARC was granted IBHE Center status in 2021 as a top state research center. GeoMARC operates as a "teaching hospital" of sorts by integrating undergraduate and graduate students into all levels of our projects. Since arriving at SIUE 30 years ago, I have fully funded over 95 graduate assistantships and hundreds of undergraduate students through student

employment and internships (with the ultimate goal of providing students with valuable "experiential learning").

2. My team and I continue to conduct advanced remote sensing research globally for companies/agencies such as the Electric Power Research Institute (EPRI), Bayer Crop Science, Illinois Corn, Illinois Department of Natural Resources, Iowa Soybean Association, PivotBio, Danforth Plant Science Center, etc., primarily related to vegetation/habitat management and assessment. Many of these research relationships span decades.

3. My team and I routinely act as external evaluators of commercial airborne and drone systems from around the US to determine their potential for developing calibrated data enabling appropriate calculation of critical vegetation indices for comparing vegetation metrics across time and across space.

4. I have been a college professor for 28 years and taught many courses pertinent to this project in the following subjects:

    a. Remote sensing and image processing

    b. Machine Learning and advanced image processing

    c. Vector GIS, Raster-based GIS, and Computer Modelling

    d. Soils

    e. Geomorphology (Landforms)

HONORS AND AWARDS

- University Teaching Excellence Award (2001) – Recognized by SIUE as the top professor across the university (one award per year).
- Emerson Electric Teaching Award (2002) – Recognized as top collegiate educator in St. Louis Region.

GEOMARC / JOSHUA G. PRITSOLAS

Senior Scientist with Specialization in Remote Sensing, GeoSpatial Mapping, Applications, and Research Center (GeoMARC)
Southern Illinois University Edwardsville (SIUE)
420 University Park Drive, Edwardsville, IL 62025
Phone: 618-650-2025
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EARNED DEGREES

Institution	Area	Degree	Year Awarded
Southern Illinois University Edwardsville	Geography	B.S.	2015
Southern Illinois University Edwardsville	Geography	M.S.	2018

EMPLOYMENT HISTORY

Years	Position
2020 – Current	Senior Scientist with Specialization in Remote Sensing, GeoMARC, SIUE
2018 – 2020	Remote Sensing Analyst, GeoMARC, SIUE
2017 – 2018	Civil Service, GeoMARC, SIUE
2015 – 2017	Graduate Assistant, GeoMARC, SIUE
2014 – 2015	Undergraduate Assistant, GeoMARC, SIUE

TEACHING EXPERIENCE

Geographic Information Systems (GIS) at Edwardsville High School through an extension program. 2015-2019.

Educational advisor to graduate students at SIUE regarding advanced applications of GIS/remote sensing. 2018-Current.

SYNERGISTIC ACTIVITIES

1. Analyzed various study plots across a growing season of different grasses, flower mixes, and management practices for EPRI and Ameren to begin establishing metrics that quantify and characterize grassland quality in a utility right-of-way using different drone and satellite sensors along with machine learning algorithms.
2. Created a workflow and developed a model to assess total potential milkweed habitat and milkweed habitat at risk to herbicide impact across the Midwest to aid Bayer Crop Science in reporting their exposure side of a risk assessment equation to government agencies for compliance purposes.
3. Developed a novel method using historic Landsat imagery along with other archived land use classification products (i.e., USDA Cropland Data Layer and the MRLC National Land Cover Database) to create millions of highly confident ground truth

labels for machine learning algorithms that were used to classify grasslands using Sentienel-2 imagery across different geographic regions of Illinois from 2010-2017.

4. Lead scientist on remote sensing project that utilized over 350 images, which mapped and characterized grasslands at two separate location in Germany to aid in the understanding of winged-insect habitat evolution over the past 25-years.
5. Worked directly with Monsanto/Bayer and Climate Corp. to assess and analyze herbicide and pesticide drift symptomology on soybeans through remotely sensed imagery over regionally various locations (over 150 farm sites) throughout the United States.
6. Managed and coordinated project objectives and was lead remote sensing specialist that processed and organized a five-year temporal database with over 10 TBs of digital aerial and drone imagery utilized in joint research efforts with Iowa Soybean Association (ISA) and Iowa State University.
7. Developed and implemented radiometric calibration techniques that utilize empirical line and segmented regression techniques with calibration tarps, and the use of pseudo invariant features for temporal comparisons.
8. Utilized novel approaches in principal component analysis (unique rotation and extraction methods) to analyze multispectral and multitemporal remotely sensed data through traditional statistical models and spatial statistical models to better understand the temporal and spatial variability of corn and soybean yield.

HONORS AND AWARDS

- Army Accommodation Medal with Valor Device (2004) – For combat operation in Baqubah, Iraq.
- Bronze Star Medal (2004) – For combat operations conducted during Operation Phantom Fury in Fallujah, Iraq.
- Abraham Lincoln Civic Engagement Award (2015) – One student from each of the 4-year degree granting universities in Illinois are honored for leadership and service in the pursuit of the betterment of humanity and for overall excellence in curricular and extracurricular activities.
- Outstanding Thesis Award (2018) – Recognized by the Graduate Student Award Committee with the outstanding thesis among all students at Southern Illinois University Edwardsville.

GEOMARC
LIST OF PRESENTATIONS, PUBLICATIONS AND REPORTS

Pritsolas, J., R. Pearson, and P. Kyveryga. 2017. “Partnership to Develop Better Imagery Products for Crop Assessment.” Iowa Soybean Association Newsroom, May Edition.

Pritsolas, J. 2018. “Principal Component Analysis and Spatial Regression Techniques to Model and Map Corn and Soybean Yield Variability with Radiometrically Calibrated Multitemporal and Multispectral Digital Aerial Imagery.” Master’s thesis. Southern Illinois University Edwardsville.

Pearson R., J. Pritsolas, and P. Kyveryga. 2018. “Differences Between Calibrated and Uncalibrated Aerial Imagery.” Iowa Soybean Association Newsroom, July Edition.

Pritsolas, J. and R. Pearson. 2019. “Critical Review of Supporting Literature on Land Use Change in the EPA’s Second Triennial Report to Congress.” Renewable Fuels Association, July News Release. https://ethanolrfa.org/file/1834/SIUE-Review-of-Land-Use-Change-Literature-07-2019.pdf.

Pritsolas, J., A. Prestholt, P. Kyveryga, and R. Pearson. 2019. “Quality of Digital Aerial Imagery and Implications for Various Uses in Agriculture.” In Proceedings of the 31st Integrated Crop Management Conference: 31-41. https://ninjaag.com/wp-content/uploads/2020/10/Quality-of-Digital-Aerial-Imagery-and-Implications-for-Various-Uses-in-Agriculture.pdf.

Werle, R., R. Pearson, J. Pritsolas, M. Oliveira and R. Rector. 2020. “Aerial Imagery as a Potential Tool to Evaluate Dicamba Off-Target Movement in Soybeans.” 60th Weed Science Society of America and Western Society of Weed Science, March 4.

Smeda, R., J. Weirich, E. Sall, R. Pearson, J. Pritsolas, and R. Rector. 2020. “Field-Scale Assessment of Dicamba Off-Target Movement from Soybeans in Missouri.” 60th Weed Science Society of America and Western Society of Weed Science, March 4.

Pearson, R., J. Pritsolas, K. Copenhaver, and S. Mueller. 2020. “Assessment of the National Resources Inventory, the Census of Agriculture, the Cropland Data Layer, and Demand Drivers for Quantifying Land Cover/Use Change.” Full Report to the Environmental Protection Agency. Southern Illinois University Edwardsville, CropGrower LLC, and University of Illinois at Chicago. https://erc.uic.edu/wp-content/uploads/sites/633/2021/06/LUC_Report_Version-3_25_2020_Updated.pdf.

Mueller, S., R. Pearson, J. Pritsolas, N. Hall, and B. Armantrout. 2021. “U.S. Reclaimed Coal Lands: An Analysis of Low Risk for Indirect Land Use Change Under the Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA).” Full Report to the International Sustainability and Carbon Certification. Southern Illinois University Edwardsville, SCS Global Services, and University of Illinois at Chicago.

Pritsolas, J. and R. Pearson. 2021. “A Cautionary Tale: A Recent Paper’s Use of Research Based on the USDA Cropland Data Layer to Assess the Environmental Impacts of Claimed Cropland Expansion.” Renewable Fuels Association, June News Release. https://ethanolrfa.org/file/1833/SIUE-Rebuttal-on-USDA-CDL-Use.pdf.

Pritsolas, J. and R. Pearson. 2021. “Assessing the Land Use Change of Wind Turbine Installations Across the Agriculturally Productive Midwestern Region of the United States.” Final Report, Illinois Corn Growers Association.

Pritsolas, J. and R. Pearson. 2022. “Ameren University Challenge: Remote Sensing Data Processing Report.” Final Report, Ameren.

Pritsolas, J. and R. Pearson. 2022. “Preliminary Results for the Bayer Milkweed Habitat Analysis in the Midwest (2019-2020) Analysis.” Update Report, Bayer.

Holmes, C. M., J. Pritsolas, R. Pearson, C. Butts-Wilmsmeyer, and T. Schad. 2023. "Time-Series Characterization of Grassland Biomass Intensity to Examine Management Change at Two Sites in Germany Using 25 Years of Remote Sensing Imagery" Applied Sciences 13, no. 22: 12467. https://doi.org/10.3390/app132212467.

Pritsolas, J. and R. Pearson. 2023. “Assessment of Various Remote Sensing Data from Pivot Bio Corn Trials.” Final Report, Pivot Bio.

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Pritsolas, J. and R. Pearson. 2023. “Assessment of CDL Certainty Over Time.” Update Report, Bayer.

Pritsolas, J. and R. Pearson. 2023. “Verification of Milkweed Habitat Modeling: Using Sentinel 2 for Land Cover Classification in Iowa.” Update Report, Bayer.

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Pritsolas, J. and R. Pearson. 2024. “Data and Methods Matter: Assessing the Differences Between Two Versions of SoilGrids250m.” Final Report, Renewable Fuels Association.

Pritsolas, J. 2024. "Geo+AI Discussion Panel – STL TechWeek." Discussion Panel at Southern Illinois University Edwardsville.

Pritsolas, J., R. Pearson, and A. Bennett. 2025. "Remotely Collected Satellite Metrics for IVM and Biodiversity Reporting." Final Report, Electric Power Research Institute. https://www.epri.com/research/programs/025032/results/3002030092.