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Multi-Criteria Evaluation Model for Classifying Marginal Cropland in Nebraska Using Historical Crop Yield and Biophysical Characteristics

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MULTI-CRITERIA EVALUATION MODEL FOR CLASSIFYING MARGINAL CROPLAND IN NEBRASKA USING HISTORICAL CROP YIELD AND BIOPHYSICAL CHARACTERISTICS

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Marginal cropland is suboptimal due to historically low and variable productivity and limiting biophysical characteristics. To support future agricultural management and policy decisions in Nebraska, U.S.A, it is important to understand where cropland is marginal for its two most economically important crops: corn (*Zea mays*) and soybean (*Glycine max*). As corn and soybean are frequently planted in a crop rotation, it is important to consider if there is a relationship with cropland marginality. Based on the current literature, there exists a need for a flexible yet robust methodology for identifying marginal land at different scales, which takes advantage of high spatial and temporal resolution data and can be applied by researchers and outreach professionals alike. This research seeks to individually identify where cropland is marginal for corn and soybean as well as classify the extent of marginality that exists. This research also seeks to classify cropland as being part of a long-term corn-soybean crop and see if marginality differs between this cropland and the remainder of cropland. Two crop-specific multi-criteria evaluations (MCE), consisting of crop production, climate, and soil criteria, was performed using Google Earth Engine to identify and classify marginal cropland. Criteria were individually thresholded before addition to the MCEs. Cropland that was classified as part of a long-term corn-soybean crop rotation was identified by factoring in the balance of corn and soybean occurrence on long established cropland.

Most cropland in Nebraska has at least some marginality for corn while most has no marginality for soybean. Marginality classification is spatially distributed with increasing marginality from the northeast to the southwest. Cropland under a long-term crop rotation shows much less marginality compared to non-rotation cropland. This study improves upon previous attempts to identify marginal cropland in Nebraska by increasing spatial and temporal resolution, providing a programmatic and replicable methodology, and confining the classification to existing cropland. The implications of these findings are useful for policy makers and agricultural extension efforts in Nebraska to identify opportunities for conservation, solar energy capture, and biofuel production on cultivated land.

DEDICATION

To my wonderful partner Mirae, whose love and support I cherish and with whom my everyday is more interesting than the last.

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CHAPTER 1: INTRODUCTION

1.1 Topic and Context

Marginal land has been a trending topic for well over a decade, especially for biofuel production in the United States and around the world (Khanna et al., 2021). However, despite its trending status, defining marginal land can be difficult as this changes based on the aim and scope of a study (Lewis & Kelly, 2014). The definition of marginal land used for this study, hereon referred to as marginal cropland, refers to cropland that is suboptimal due to historically low and variable productivity and limiting biophysical characteristics. This definition differs from many studies, as they do not constrain the classification to a single land class such as cropland (Gopalakrishnan et al., 2011; Kang et al., 2013; Lewis & Kelly, 2014; P. Yang et al., 2020). The constraint on land classification is important as cropland expansion during the last two decades often results in cropland that produces less than average yields and harmful impacts to wildlife nesting and living habitat (Lark et al., 2020).

Marginal land has been highly sought after for biofuels production, in particular for the growth of perennial biomass crops such as switchgrass (*Panicum virgatum*) and miscanthus (*Miscanthus sp.*) (Feng et al., 2017). This was driven in part by concerns that biofuel production could reduce grain production and raise grain prices, especially if biofuel crop prices caused displacement of food crops on the highest quality land (Elobeid & Hart, 2007; G. Cassman & Liska, 2007; Swinton et al., 2011). Perennial biomass crops also offer important environmental benefits such as improved soil health, wildlife habitat, and carbon sequestration (Augustenborg et al., 2012; Swinton et al., 2011). However, the focus on biofuel production has overshadowed other opportunities for marginal cropland which include conservation practice and solar energy capture.

Conservation practices such as conservation tillage, crop rotations, and cover crops have shown improved soil health, crop yields, and reductions in nutrient loads in streams (García et al., 2016; Nunes et al., 2018). Conservation practices can often be integrated into existing cropping systems with minimal changes and assistance, both technical and financial, offered by university extension and government programs. In the U.S., many of these programs are administered by two agencies within the U.S. Department of Agriculture (USDA), the Natural Resources Conservation Service (NRCS) and the Farm Service Agency (FSA). Such programs include the Environmental Quality Incentives Program (EQIP) from the USDA-NRCS and the Conservation Reserve Program from the USDA-FSA. However, there is a complex system of motivations and barriers that influence farmers' willingness to adopt conservation practices (Ranjan et al., 2019). This complex system is becoming increasingly studied, resulting in insights that intend to contribute to the application of conservation practices on marginal cropland.

Interest in solar energy capture on existing or abandoned croplands is growing, both from consumers and researchers. Croplands are ideal for solar power as they are often flat, contain nearby access roads, and access to electric transmission lines. Marginal croplands, particularly large expanses, are prime candidates for agrivoltaic systems, which combine crop production with solar power generation (Macknick et al., 2013). Agrivoltaic systems could improve economic returns through increased land-use efficiency, allow for continue food grain production, and even support growth of perennial biofuel crops such as switchgrass with the right installation considerations

(Macknick et al., 2013; Proctor et al., 2020; Tsai et al., 2020). While solar energy capture on cropland faces some issues such as local zoning codes and crop shading and requires additional study, it offers another potential use case for marginal cropland.

1.2 Focus and Scope

Nebraska was chosen as the study area due to the importance of agriculture, both socially and economically, to the state. Agriculture accounts for 92% of the state's land area, 22% of the gross state product, and a quarter of its jobs (Nebraska Department of Agriculture, 2021; Thompson et al., 2020). Cropland is the one of the largest land use classifications in Nebraska, accounting for 47% of the state's land area (51% of all agricultural land) (Nebraska Department of Agriculture, 2021). Two crops, corn (*Zea mays*) and soybean (*Glycine max*), are the focus of this research as they are the two most valuable crops in terms of yearly production (Thompson et al., 2020). Therefore, understanding the extent of marginal cropland for each crop is important for guiding future agricultural policy, management practices, and outreach efforts in the state of Nebraska. However, the application of policy and practice on marginal cropland requires understanding underlying cropland characteristics at scales useful for outreach and research. A study period from 1999-2018 and final spatial resolution of 30 meters was pursued to take advantage of current, publicly available datasets while accounting for long-term trends and state and field-level considerations.

1.3 Background

Marginal land has been studied with differing methodologies and definitions. What follows is a selection of these methods and definitions with commentary on advantages and/or weaknesses. Gopalakrishnan et al. (2011) sought to identify marginal land in Nebraska using economic, soil health, and environmental criteria. The study found that over 1.6 million hectares of land in Nebraska could be classified as marginal for two or more of the criteria (Gopalakrishnan et al., 2011). A novel method for identifying marginal land at the time, Gopalakrishnan et al. (2011) provided an original method that considered new areas such as highway or right-of-way medians, brownfield sites, and areas with nitrogen contamination from runoff. However, some issues present in the study include relying on the National Commodity Crop Productivity Index, which is derived by underlying soil characteristics for rainfed cropland, as well as not considering the influences of climate or irrigation (Gopalakrishnan et al., 2011).

Peter et al. (2018) developed a model to identify marginal agricultural land for corn that was generalizable for decision making at different spatial scales. This study used long-term productivity, biophysical characteristics, and temporal climactic thresholds. This methodology also sought to manage issues brought on by the modifiable areal unit problem, errors of commission, and the ecological fallacy problem (Peter et al., 2018). The key addition to marginal land identification was the generalizability at different spatial scales which was accomplished by using a quantile classification algorithm for yield. The quantile classification can also be applied to other non-binary characteristics to generalize at-scale.

Machine learning has been applied to mapping marginal land by several recent studies. Yang et al. (2020) used biophysical properties, including climate, soil, and land slope, to estimate their impact on yields of six major crops across the continental United States (CONUS). The result was a machine learning derived, unconstrained map of productivity potential across CONUS at a 250-meter resolution. Yang et al. (2021)

expanded beyond productivity and biophysical predictors by incorporating a socioeconomic input derived from a study of farmers' perceptions of marginal land. These were used to train a machine learning model and derive maps of marginal likelihood and the underlying issues at a 250-meter spatial resolution on agricultural land. While both methods take advantage of the predictive capabilities of machine learning, the spatial resolution of their outputs are coarse for making decisions at the subfield level. Additionally, applying machine learning solutions requires a level of expertise that is not always available to all users.

Based on the current literature, there exists a need for a flexible yet robust methodology for identifying marginal land at different scales, which takes advantage of high spatial and temporal resolution data and can be applied by researchers and outreach professionals alike. The methodology should consider criteria that are relevant to cropland and thresholds guided by crop considerations where applicable. The methodology should replicable and the results understandable without the need for advanced statistical or machine learning knowledge. Finally, a conversation about crop rotation and marginal cropland has been lacking in the literature and should be examined.

1.4 Research Questions

Based on the considerations put forth by the literature and the identified knowledge gap, the following research questions are considered in this study:

1) For corn and soybean, where can marginal cropland be identified for each crop specifically using historical crop yield and biophysical criteria?

2) For the land identified as marginal, what classification of marginality is present: none, low, moderate, or high?

    - What are the spatial trends of cropland marginality classifications for each crop?
    - Are there any relationships between the spatial trends of cropland marginality and farmland prices?

3) Where can a long-term crop rotation (corn-soybean) on cropland be classified?

    - What temporal period or temporal crop occurrence ratio will sufficiently identify cropland that experience the benefits of long-term crop rotations?

4) Does marginality differ between cropland under a long-term crop rotation (corn-soybean) and cropland not under a long-term crop rotation?

The method proposed in this research considers the inputs of productivity and biophysical predictors, including climate and soil characteristics, while leaving open the option for adding socioeconomic inputs as they become available at scales useful for field-level application. Long-term crop rotations will be identified to further understand their interactions with marginal cropland, which has not been well studied. Identifying long-term crop rotations will also help target solutions that take advantage of crop rotations. To aid in applicability to other spatial extents and scales, the final methodology will be made available through Google Earth Engine (GEE).

CHAPTER 2: METHODS

2.1 Analytical Model and Technology

A crop-specific multi-criteria evaluation (MCE) was chosen as the analytical model due to its frequent use for suitability analysis and for identifying potential marginal land use (Malczewski, 2004; Voivontas et al., 1998). As the analytical model seeks to be adaptable and straightforward for broader use, the model uses unweighted, boolean overlays for the final classification. boolean overlays for each model were either procured input-ready or processed into boolean images using thresholding or a set of conditional determinants. Overlays with temporal stacks were aggregated using mean or summary values. A cropland mask was applied to the final classification to constrain the analysis to existing cropland due to environmental and productivity concerns of cropland expansion (Lark et al., 2020).

Tabular data inspection and cleaning for ingestion into GIS was done using Microsoft Excel (*Microsoft Excel*, 2021). White space was removed from the tops of tables, column headers formatted, and column data types set in Excel. Disparate worksheets representing agricultural fields were combined into a single worksheet. Spatial data preprocessing and creation was handled using Python Notebooks in ESRI's ArcGIS Pro, which was also used for map creation (ESRI, 2021). Tabular ENREC yield data was ingested into a Spatially Enabled DataFrame (SEDF) inside ArcGIS Pro using Python, all null cells converted to zeroes, and yearly point feature layers of yield created from latitude and longitude columns in the SEDF. Finally, a Python script was run to convert each yield feature layer to a 30-meter spatial resolution raster of yield using a mean bilinear interpolation.

Google Earth Engine (GEE) was chosen as the primary GIS to perform the MCE due to the large number of available datasets, cloud computing capabilities, and ability to ingest user data (Gorelick et al., 2017). GEE allows for analyzing spatial and temporal trends through an integrated code editor written in Javascript but there also an official Python API in addition to Python and R libraries created by other developers (Aybar et

Table 2.1: Summary of masking images and thresholds.

Mask	**Dataset(s)**	**Classification Thresholds**	**Spatial Resolution**	**Temporal Resolution**	**Source**
Cropland	CSDL	≥ 1 year of cropland between 2015-2018	30 m	1 year	Wang et al. 2020
Irrigation Status	LANID-US	Irrigated: ≥0.5 mean pixel value for years of irrigation between 1999-2018 Rainfed: ≤ 0.5 mean pixel value for years of irrigation between 1999-2018	30 m	1 year	Xie and Lark 2021

al., 2020; Wu, 2020). Data and images were exported from GEE to Google Drive while data was analyzed and visualized using Python in Google Colaboratory (Bisong, 2019).

2.2 Constraint Masks

The cropland mask was created using the Corn-Soy Data Layer (CSDL) (Table 2.1) (Wang et al., 2020). First, the CSDL was filtered to images corresponding to the years 2015-2018. Next, the temporal stack was reduced to a single image, with pixel values greater than or equal to 1 signally where cropland occurred at least once during the period, then clipped to Nebraska. The 2015-2018 time period was chosen to capture the latest trends in cropland expansion, take into consideration fields that go in and out of fallow status, and account for the conversion of cropland to residential use near urban areas (Lark et al., 2020). As mentioned above, the cropland mask is used to constrain results of the MCE and for intermediate analysis.

The irrigation status mask was created using the Landsat-based Irrigation Dataset for the United States (LANID), which maps irrigation on a yearly basis from 1999-2017 (Table 2.1) (Xie & Lark, 2021). Image bands contain boolean pixel values for irrigation status, with 1 corresponding to an irrigated pixel and 0 a rainfed pixel. A cumulative pixel value for the temporal stack was calculated and values greater than or equal to 13, which represents most of the temporal stack being irrigated, labelled as under long-term irrigation. There are several assumptions considered with this calculation. First, the capital cost of irrigation systems would prevent user drop-out if the system remains in an operational condition. Second, irrigated land under the purview of a permitting agency or other top-down governance may use a non-consecutive irrigation regime in response to restrictions on agricultural water use (J. Luck, personal communication, 9/24/2021; T.

Franz, personal communication, 9/24/2021). Lastly, irrigation plays an important role in agriculture, allowing crops to grow during extreme climate conditions and raising the threshold for negative impacts on yield compared to rainfed (Lobell et al., 2009; Troy et al., 2015). As the MCE looks at long-term impacts, the resulting impacts on yield could be better parsed using this calculation.

2.2 Criteria

The criteria chosen for the final crop-specific MCE were productivity, heat stress, slope, soil organic content, available water storage, droughty soils, ponding soils, and root zone depth. The criteria broadly represent four categories: economic returns (yield), climate (heat stress), accessibility and safety of cropland (slope) and soil and soil health (soil organic content, available water storage, droughty soils, ponding soils, and root zone depth). Most of the criteria chosen are common to other studies on marginal land.

2.2.1 Productivity

2.2.1.1 Mean Crop Yield

Yield calculation has been done using a semi-empirical model by converting remote sensed accumulated biomass to final yield using a crop-specific conversion equation (Jaafar & Ahmad, 2015; Marshall et al., 2018). This requires an observation of a specific crop in time and space and a measurement of the accumulated biomass. The CSDL dataset was chosen to meet the first requirement as it contained yearly observations of corn, soybean, and cropland from 1999-2018. The CSDL was chosen over the commonly used USDA National Agricultural Statistical Service (NASS) Cropland Data Layer (CDL) as the CSDL allows for longer temporal analysis due to its increased accuracy and coverage from 1999-2007 (Wang et al., 2020). CSDL has

Table 2.2: Summary of MCE criteria thresholds and datasets.

Criteria	Dataset(s)	Marginal Threshold		Spatial Resolution	Temporal Resolution	Source
		Corn	Soybean			
Yield	CSDL Landsat GPP	< 33rd percentile mean 20-year yield and < 50th percentile 20-year standard deviation of yield per irrigation class		30 m 30 m	1 year 16 day	Wang et al. 2020 Robinson et al. 2018
Heat Stress	Daymet V4	≥14 years with ≥6 days with a T_{max} ≥ 33.8°C during the silking period	≥14 years with ≥6 days with a T_{max} ≥ 35.0°C during flowering and early grain filling period	1000 m	1 day	Abatzoglou 2013
Slope	3DEP DEM	6° or 12%		10 m	N/A	USGS 2021
Ponding	gSSURGO	Pixel values greater than 0.33		10 m	N/A	USDA-NRCS 2021
Droughty	gSSURGO	Pixel value of 1		10 m	N/A	USDA-NRCS 2021
Root Zone Depth	gSSURGO	<150 cm	<90 cm	10 m	N/A	USDA-NRCS 2021
Available Water Storage	gSSURGO	18.8 cm of AWS in 0-150 cm soil horizon	12.5 cm of AWS in 0-100 cm soil horizon	10 m	N/A	USDA-NRCS 2021
Soil Organic Content	gSSURGO	< 25^{th} percentile $SOC_{score30,150}$	< 25^{th} percentile $SOC_{score30,100}$	10 m	N/A	USDA-NRCS 2021

consistent observations with CDL from 2008-2018 due in part to CSDL using CDL and Landsat imagery to train a machine learning model to perform hindcasting (Wang et al., 2020). An additional benefit is that CSDL is readily available in GEE. An example of the CSDL dataset can be seen in Figure A.2.

Accumulated biomass is often represented by one of two values: gross primary productivity (GPP) or net primary productivity (NPP). GPP is a measurement of the fraction of photosynthetically active radiation that is absorbed by vegetation throughout the growing season. NPP is GPP minus the energy lost to the environment through respiration costs. Other research has used NPP to calculate yield but early work in this study and others showed that using NPP often resulted in low yield estimation (Reeves et al., 2005; Xin et al., 2013). These measurements came from the Landsat Gross Primary Productivity CONUS (Landsat GPP) dataset by the University of Montana Numerical Terradynamic Simulation Group (Robinson et al., 2018). An example of the Landsat GPP dataset can be seen in Figure A.3.

Gross primary production was initially converted to crop production (tonnes) using a harvest index (HI), root: shoot ratio (R:S), moisture content (MC), and the area represented by the pixel (A_{px}), an adaptation of Prince et al., 2001:

$$(Eq\ 2.1) \quad Yield = GPP \times \frac{HI}{1+RS} \times \frac{1}{1-MC} \times A_{px}$$

Initial testing at the field scale showed the need for a crop-specific correction coefficient (Y_c), which led to the final equation:

$$(Eq\ 2.2) \quad Yield = GPP \times \frac{HI}{1+RS} \times \frac{1}{1-MC} \times A_{px} \times Y_c$$

Table 2.3: Crop-specific values for yield calculation.

Crop	**HI**	**RS**	**MC**	**A_{px}**	**Y_c**
Corn	0.53	0.18	0.11	0.09	1.585194402
Soybean	0.42	0.15	0.1	0.09	0.719686173

Crop-specific values for HI, RS, MC, and Y_c can be found in Table 2.3. Y_c was calculated for each crop by summing combine harvester yields and calculated yields across all available years of ENREC data, calculating the relative difference between combine harvester and calculated yields, and adding 1. Y_c, though a simple method of correction, was applied to yield calculation at the state level because of several concerns, which included: spatial location of ENREC with regards to the spatial extent of Nebraska and whether ENREC is represesentative of such broad conditions; small sample sizes of crop yield collected from only three fields and fifteen years of data; and limited abilities to infer rainfed effects on crop-specific yield as the rainfed field alternates crop plantings. The temporal stack was aggregated to find the mean yield for each crop type. Pixels were then grouped into irrigated and rainfed pixels using the *irrigation status* masking layer. Pixels with values less than the intragroup 33rd percentile are given a value of 1 (Gopalakrishnan et al., 2011; Peter et al., 2018).

2.2.1.2 Yield Variability

Yield stability is important as it shows that an area provides consistent economic returns. Pixels were divided into two groups, stable or variable. This was done by calculating the standard deviation of yield of a crop-specific temporal stack. Pixels were then grouped into irrigated and rainfed pixels using the *irrigation status* masking layer. Pixels with values greater than the intragroup 50th percentile are given a value of 1 (Peter et al., 2018).

2.2.1.3 Combined Productivity Overlay

The final productivity criteria image was created by intersecting the pixels with the lowest yields with the most variable pixels (Table 2.2). The mean crop yield and yield variability images were added together, and overlaps were indicated by a pixel value of 2 in the resulting image. Values of 2 were reclassified to a value of 1 with all other values reclassified to a value 0 and masked to cropland for the final productivity image before addition into the MCE.

2.2.1.4 Analysis and Validation

Two data sources were used to verify productivity calculations at separate scales (Table 2.4). At the field level, crop production from the Eastern Nebraska Research and Extension Center (ENREC) was used to calculate Y_c (Franz et al., 2020). Data was available across a nineteen year period (2000-2018) and three fields under different cropping regimes: irrigated straight-cropped corn, irrigated corn-soybean rotation, and rainfed corn-soybean rotation (Franz et al., 2020). This data was preprocessed and made spatial using Excel and ArcGIS Pro then ingested into GEE, as described in Section 2.1. At the county-level, yield data was retrieved from the NASS Quick Stats database for both grain and silage then summed into a single yield value (*NASS - Quick Stats*, 2021). Yearly state aggregated NASS yield estimates and calculated yields were graphed with

Table 2.4: Summary of yield verification datasets.

Scale	**Dataset(s)**	**Temporal Resolution**	**Source**
Field	ENREC Harvest Data	1 year	Franz et al. 2020
County/State	NASS Crops/Stocks Agricultural Survey	1 year	NASS - Quick Stats 2021

linear regression trendlines to visually compare the slopes of each data source over time (Figure 3.2).

Wang et al., 2020 provides validation of cropping area totals against CDL and NASS statistics. With using CSDL as the observation source, yield trend validation against CDL and NASS yield estimates from 2008-2018 was deemed a prudent step. Yield was calculated using Eq2 but the source of observations coming from two different sources, CDL and CSDL, across 2008-2018. Yield was summed at the state-level resulting in two calculated datasets ($Yield_{CSDL}$ $Yield_{CDL}$). $Yield_{CSDL}$, and $Yield_{CDL}$ were graphed with linear regression trendlines to visually compare the slopes of each data source over time (Figure 3.3).

2.2.2 Climate

2.2.2.1 Heat Stress

Heat stress can have major impacts on crop growth on rainfed cropland but less so on irrigated cropland due to irrigation raising the thresholds for plants to experience stressors (Table 2.2) (Lobell et al., 2009). Despite the positive impacts of irrigation, this criterion was not restricted to rainfed cropland as Nebraska has had concerns over water extraction for cropland irrigation. This concern spans a lawsuit from Kansas over the Republican River water depths and potential overextraction of the Ogallala Aquifer and impacts of climate change on these practices (Abrams, 2014; Deines et al., 2020).

Crop-specific heat stress was determined by examining at what growth stage a temperature can impact final yield if experienced for a specific duration (Table 2.5) (L. Puntel, personal communication, October 26, 2021). Corn is most susceptible during the

Table 2.5: Crop-specific thresholds for heat stress criteria.

Threshold	Crop	
	Corn	**Soybean**
Start DOY	163	163
End DOY	225	212
Temperature	33.8°C/93°F	35°C/95°F
Duration	6 days	6 days
Years	14	

silking phase (DOY 163-225) (Elmore & Taylor, 2011; Herrero & Johnson, 1980; National Agricultural Statistical Service, 2005). Maximum daily temperatures over 33.8°C for 6 or more days can reduce corn crop yield 4-10% (Elmore & Taylor, 2011). Soybean is most susceptible during the flowering and early grain filling (DOY 163-212) at temperatures above 35°C (Gibson & Mullen, 1996; National Agricultural Statistical Service, 2005; Vann, 2020). Durations for soybean was matched to corn as durations in the literature were generalized.

The crop-specific heat stress images were created by filtering the Daymet V4 images to the day of year (DOY) range and year range (1999-2018) (Table 2.2). The 6-day average of the daily maximum temperature was calculated and values greater than the temperature threshold assigned a value of 1. The temporal stack was summed by year and 1 or more occurrences of a heat stress event led to that year receiving a value of 1 and no occurrences a value of 0. The interannual temporal stack was then summed and pixel values greater than 14, representing a significant majority of 20 years, were remapped to a value of 1 and all others to 0. The final heat stress criteria image was reprojected to a 30-m resolution using mean resampling and masked to cropland. An example of the Daymet V4 dataset can be seen in Figure A.4.

2.2.2.2 Precipitation

Precipitation constraints are of prime concern for crops grown on rainfed cropland, as noted above. Precipitation was considered but not included in the final MCE due to lack of significant results during testing. Two methods were considered to examine marginality for precipitation: 20-year mean growing season accumulated precipitation and prevalence of large precipitation events during the early growth stages of the crops (L. Puntel, personal communication, October 26, 2021; Peter et al., 2018). Accumulated precipitation was discarded due to difficulties with defining thresholding ranges for the area of study. Prevalence of large precipitation events was tested but early results showed that the large precipitation events during early growth stages had not occurred during the temporal window and across the area of study.

2.2.3 Soils

2.2.3.1 Data Preprocessing

The Gridded Soil Survey Geographic (gSSURGO) Database is available by state as an ESRI file geodatabase from the USDA NRCS Geospatial Data Gateway (Soil Survey Staff, 2021). gSSURGO is a source of field-validated soil information across broad spatial extents in the United States. The data for Nebraska was downloaded and brought into ArcGIS Pro. Images for the criteria were extracted by joining the *Valu1* and *muaggatt* tables to the *MapunitRaster_10m* raster and exporting the resulting images with integer pixel values. After ingestion as a GEE Asset, the images were reprojected to a 30-m resolution using mean resampling and to WGS84 (EPSG: 432). WGS84 was used to match the native geoprocessing coordinate reference system in GEE. An example of the gSSURGO dataset can be seen in Figure A.5.

2.2.3.2 Root Zone Depth

Root zone depth (RZD) is a measurement of how deep within a soil profile crop roots can extract water and nutrients for growth, which significantly effects soil productivity potential (Table 2.2) (Dobos et al., 2012). From Dobos et al., 2012: “Soil component horizon criteria for root-limiting depth include: presence of hard bedrock, soft bedrock, a fragipan, a duripan, sulfuric material, a dense layer, a layer having a pH of less than 3.5, or a layer having an electrical conductivity of more than 12 within the component soil profile”. The effective root zone depths for corn and soybean were 150 cm and 90 cm, respectively (Kranz et al., 2008; Kranz & Specht, 2012). Depths less than these thresholds were classified as marginal in the root zone depth input layer then masked by *cropland* for the crop-specific MCE. Of note, while 90 cm is the effective root zone for soybean and threshold for RZD marginal classification, other depths are used for measuring soil properties in gSSURGO. The nearest depth in gSSURGO is 100 cm and this was used for soybean when considering other soil properties.

2.2.3.3 Droughty

The droughty image describes soils that are drought vulnerable, with the following definition coming from the gSSURGO metadata: “Drought vulnerable soil landscapes comprise those map units that have available water storage within the root zone for commodity crops that is less than or equal to 6 inches (152 mm)” (Table 2.2) (Soil Survey Staff, 2021). These effects are predominantly seen under climactic drought conditions and is especially impactful on rainfed cropland (Chen et al., 2010). The image comes already classified and was masked using the *cropland* mask for use in the MCE.

2.2.3.4 Available Water Storage

While available water storage (AWS) is used to identify droughty soils, it is important also consider it separately for two reasons: first, the root zone for commodity crops in the droughty calculation is assumed to be 150 cm; second, understanding where soils are overly drained is important for targeting management practices and funding (Table 2.2) (Soil Survey Staff, 2021). Overly drained soils contain AWS of approximately 1.5 in/ft or less, resulting in a threshold of 12.5 cm for soybean and 18.8 cm for corn. Soils at each crops root zone depth with AWS less than these thresholds were classified as marginal and the layer masked using the cropland mask for use in the MCE.

2.2.3.5 Ponding

The ponding images represents the frequency of ponding the soil components will experience over a unit of time (Table 2.2) (Soil Survey Staff, 2021). A threshold frequency of 33% or greater was chosen as this represents the chance of flooding occurring at least once every 3 years and represents a significant risk to producer income. This threshold includes the upper part of the “Occasional” and all of the “Frequent” Ponding Frequency Class according to the National Soil Survey Handbook (Soil Survey Staff, 2019). This threshold was applied to the ponding image and then constrained using the *cropland* mask for the MCE.

2.2.3.6 Soil Organic Content

Soil organic content (SOC), often measured as the amount of carbon in the soil, is an important consideration for soil health (Table 2.2). The positive effect of soil organic content on crop yield has historically been attributed to the ability of SOC to supply crops with nitrogen and water nearer to the surface and improve root aeration and mitigate compaction throughout the entirety of the root zone (Kane et al., 2021; King et al., 2020). High SOC has economic benefits including reduce yield variability and lessening insurance payments during drought years (Kane et al., 2021; Lal, 2020). Generally, more SOC was considered better but thresholds for SOC were expressed not as a rate or measurement but as a percentage of soil and management practice dependent (Lal, 2020).

Soil depth is important when considering SOC impacts, as 45-60% of SOC is found in the top 30 cm of soil (Coulter et al., 2009; Y.-Y. Yang et al., 2020; Zomer et al., 2017). With a higher concentration of SOC and the importance of SOC from seeding through plant growth, the 30 cm soil horizon is highly impactful on plant health (Coulter et al., 2009). However, the SOC found throughout the remainder of the root zone needs to be considered for its impact on later vegetative stages (King et al., 2020). To take into consideration each zone and their relative importance, a soil organic content score (SOC_{score}) is calculated. This is done by manually identifying outliers through a histogram, clamping outliers to the lower and upper normalized bounds, and scale normalizing the SOC content of the 0-30 cm horizon ($Norm_{30}$) and remainder of the crop specific RZD ($Norm_{RZD}$). SOC_{score} is then calculated using those scores in a weighted formula:

$$(Eq2.3) \quad SOC_{score} = \left({}^{2}\!/_{3} * Norm_{30}\right) + \left({}^{1}\!/_{3} * Norm_{RZD}\right)$$

The weighting in the formula is based on perceived importance from the literature rather than empirically driven. The final SOC criteria input layer is calculated by reclassifying SOC_{score} pixel values less than the 25th percentile to a value of 1 and masked to cropland.

2.2.4 Slope

High slopes can make land difficult to access or dangerous to farm with modern farming equipment. Previous studies have used thresholds anywhere between 5-12 degrees (10-20%) slope and conversations with experts on Nebraska soils and topography helped narrow the threshold to 6 degrees (L. Puntel, personal communication, October 26, 2021; Lewis & Kelly, 2014; Neil Dominy, personal communication, July 13, 2021). Slope was calculated with the 3D Elevation Program (3DEP) 10-Meter Resolution Digital Elevation Model using the ee.Terrain.slope function in Google Earth Engine and the image reprojected to a 30-m resolution using mean resampling (U.S. Geological Survey, 2020). Slopes greater than or equal to 6 degrees were reclassified as 1 and all other slopes to 0. The resulting layer was masked to cropland to create the final layer for the MCE. An example of the USGS 3DEP DEM dataset can be seen in Figure A.6.

2.3 Marginal Classification

With an image representing whether cropland in Nebraska is marginal for each criterion, the next step was classification. For each crop-specific MCE, the criteria images were overlaid then summed and a total score calculated, ranging from 0 to 8. This score represents the number of overlapping criteria a pixel is marginal for. To make the total scores more understandable, the scores were divided into descriptive ordinal

Table 2.6: Marginal classification score ranges.

Marginal Classification	**Score Ranges**
None	0
Low	1-2
Moderate	3-4
High	5-8

marginal classifications as detailed in Table 2.6. The total area (hectares) and percentage of cropland per class, criterion, and crop were then calculated. A comparison of spatial trends in cropland marginality and farmland prices across Nebraska is examined.

2.4 Long-term Crop Rotation

Identifying long-term corn-soybean crop rotation (LCR) is used to understand differences in marginality between LCR and non-LCR cropland as well as potential for conservation practices such as adding winter wheat or other crops to the corn-soybean

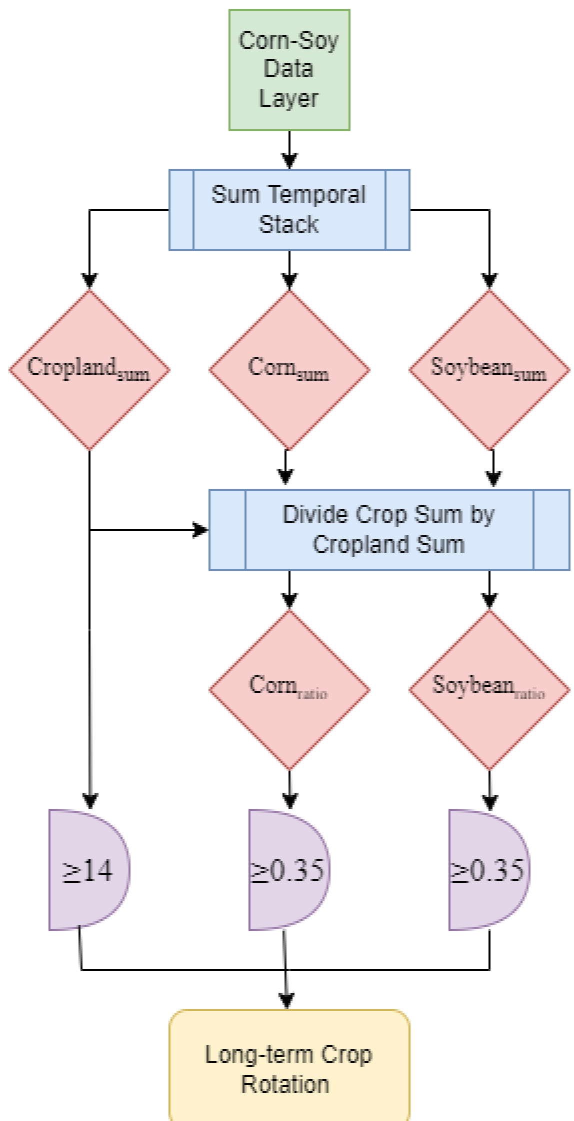


Figure 2.1: Classifying long-term crop rotation.

crop rotation (Bullock, 1992; Gaudin et al., 2015). Using a crop rotation for corn and soybean has positive effects on yield, soil physical properties, organic content, pest control, and nutrients such as nitrogen when compared to straight cropping systems (Bowles et al., 2020; Bullock, 1992; Crookston et al., 1991). However, the number of years before a crop rotation is considered long-term and benefits are seen is not clearly defined, as studies look at the effects of crop rotation across different time horizons (Bowles et al., 2020; Crookston et al., 1991). Therefore, LCR is formalized, with the input from L. Puntel (L. Puntel, personal communication, October 26, 2021), in the following way.

The CSDL was the source of observations for the productivity criteria and for formalizing LCR. For a temporal stack to be considered under LCR, it was determined that a significant majority of years with approximately equal representation of corn and soybean observations and total corn-soybean observations occurring in at least 70% of the temporal stack had to be present (L. Puntel, personal communication, October 26, 2021). First, a new image was created where CSDL was reclassified so cropland pixels equaled 1 and non-cropland 0 then the temporal stack summed to give a total of years that cropland ($Cropland_{sum}$). Next, a new image was created where CSDL was masked to each crop then the temporal stack summed to give a total number of years each crop was grown ($Corn_{sum}$, $Soybean_{sum}$). Next, an image was created that expressed the ratio of each crop across the temporal stack by dividing its sum by the crop's sum ($Corn_{ratio}$, $Soybean_{ratio}$). The following conditional statement was used to determine the presence of LCR on a pixel stack:

$$(Eq. 2.4)\ LCR = Cropland_{sum} \geq 14\ AND\ Corn_{ratio} \geq 0.35\ AND\ Soybean_{ratio} \geq 0.35$$

The classification process is illustrated in Figure 2.1. Finally, with cropland classified as either LCR or non-LCR, the percentage within-class cropland by marginal classification and marginal criteria were calculated.

2.5 Example Sites

Four example sites were selected from around Nebraska to better illustrate the methodology and selection was based on local heterogeneity in marginal classifications, quantities of marginal classification, irrigation patterns, long-term crop rotation patterns, and local features of interest. The sites are each approximately 4 miles by 4 miles (16 mi^2) and are around the same size as sixteen Public Land Survey System (PLSS) sections. The percentage of each sites total area that are under long-term irrigation and crop rotation as well as are impacted by each criterion were calculated. The impact of the different influences on marginality and agricultural practices are then examined as well as recommendations for potential uses for marginal cropland at the sites.

The Northeast site, located in Antelope County, was chosen for its closeness to the least marginal land for corn and soybean in Nebraska as well as its similar spatial patterns of marginality classification between corn and soybean. The Southeast site, located in Richardson County, was chosen to highlight an area that has traditionally been rainfed agriculture as well as the influence of heat stress on corn marginality classifications. The Central site, located in Phelps County, was chosen to represent agricultural areas near river systems or underlaid by riverine soils. Finally, the Southwest site, located in Chase County, was chosen as it highlights higher marginality classifications, limited long-term crop rotations, and is an area heavily influenced by underlying soil characteristics.

CHAPTER 3: RESULTS AND DISCUSSION

3.1 Productivity

3.1.1 Field Scale and Correction

Initial testing at the field scale using NPP resulted in yields that averaged ~20% of actual, which has been noted as an issue with final yield calculations and NPP (Reeves et al., 2005; Xin et al., 2013). When the source of biomass was switched to GPP, calculated yields were still low at the field level for corn but were higher than actual for soybean (blue line in Figure 3.1). Of note, field scale data were unavailable for 2009 and 2010 due to crop damage and data loss issues. As long-term mean crop yield is used in the Productivity criteria and the calculations were followed similar trends, an average correction coefficient based on mean accumulated yield (Y_c) was calculated.

Y_c for corn was calculated as 1.6594 and 1.5101 for irrigated and rainfed, respectively. Y_c for soybean was calculated as 0.7343 and 0.7087 for irrigated and rainfed, respectively. To avoid overfitting and issues with scaling the equation, a final Y_c of 1.5852 and 0.7197 was calculated for corn and soybean, respectively. The results of this correction at the field level are seen in Figure 3.1 as the green line, which shows much agreement over time with the red line (combine harvester).

There are some limitations to this correction coefficient. Management practices, which differ among the three fields, and other biophysical characteristics were not factored into Y_c (Franz et al., 2020). This was due to wanting to maintain similar calculation methodologies at larger scales, where management practices are difficult to account for. Also, the combine harvester data from ENREC is from 3 fields in eastern

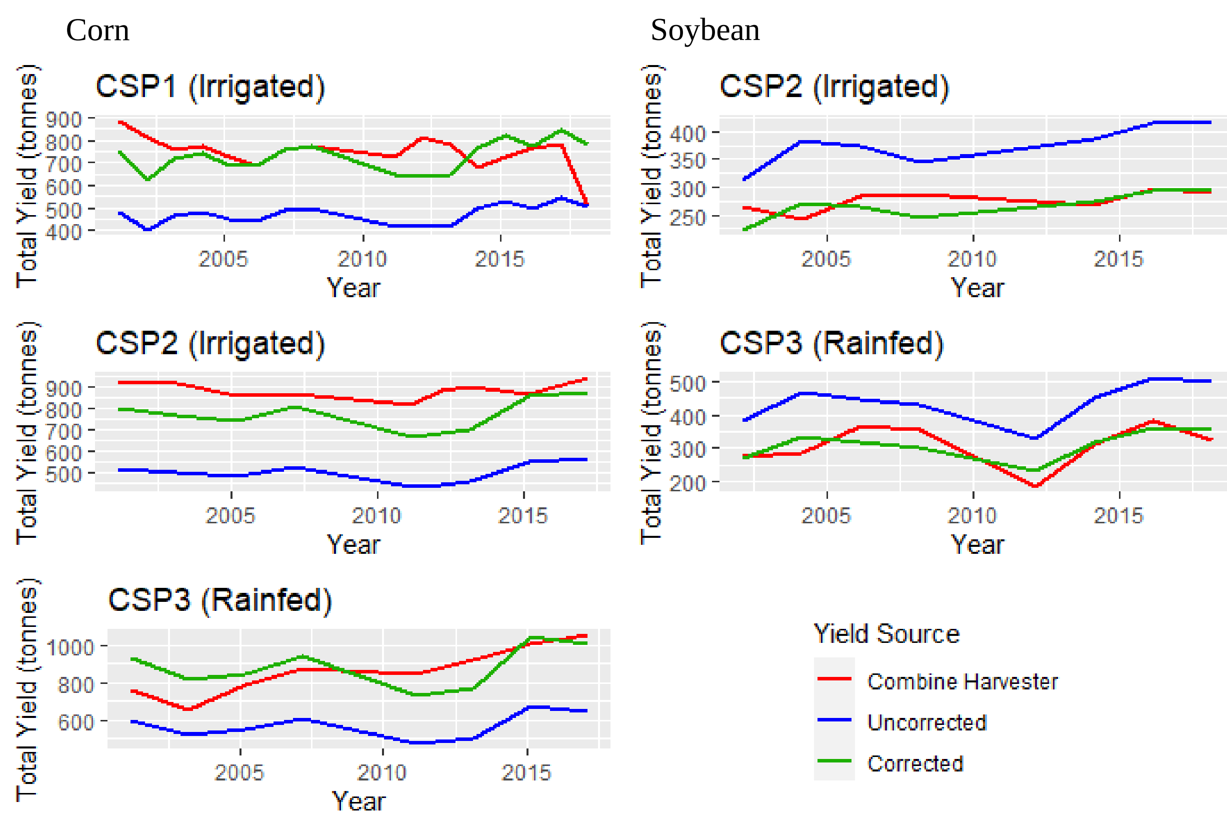


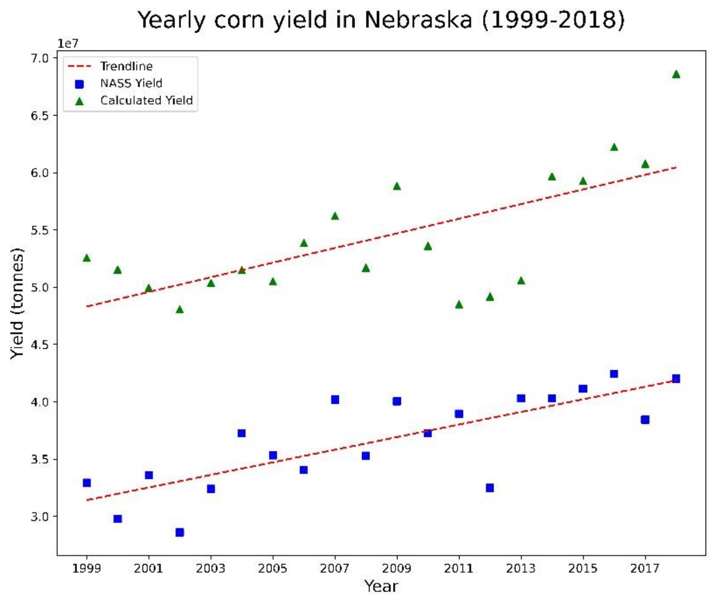
Figure 3.1. Crop yield comparisons at ENREC (2000-2018).

Nebraska and may not be entirely representative of the entirety of Nebraska. Therefore, advanced methods for correcting yield may not be more accurate for other spatial extents.

3.1.2 State Scale Comparisons

At the state scale, calculated corn yields show similar long-term and interannual trends to NASS estimates from 1999 to 2018. Calculated soybean yields also have similar long-term and interannual trends, though three years, 2002, 2012, and 2018, contain high disagreement. This is explained in part as 2002, 2012, and 2018 were all years the CSDL has low R^2 when compared with NASS soybean cultivation acreage in Nebraska (Wang et al., 2020, Figure 5).. Additionally, Nebraska experienced extreme droughts in 2002 and 2012, which could have negative impacts on vapor pressure deficit values in the underlying calculation of GPP over cropland (Marshall et al., 2018). Together, disagreement between CSDL and NASS acreage totals as well as extreme climactic events create high single year disagreement. However, these single year outliers are mitigated in the model by using long-term means across an individual pixel temporal stack, which lessens outlier interactive effects in the final criteria layer.

While long-term trends are similar between CSDL and NASS, estimated interannual yield totals are higher with CSDL with corn and higher outside of extreme climactic years for soybean (Figure 3.2). Some of this discrepancy can be explained by examining how NASS creates the estimates and past studies on NASS yield accuracy. NASS uses a combination of farmer surveys and yield modeling during and after the growing season to estimate productivity (*The Yield Forecasting Program of NASS*, 2012). NASS yield estimates are widely used, from market analysts to agricultural researchers,



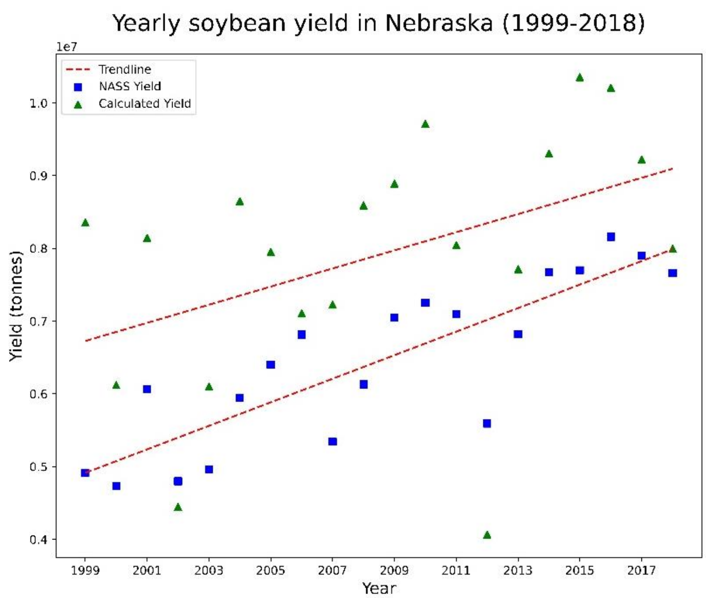
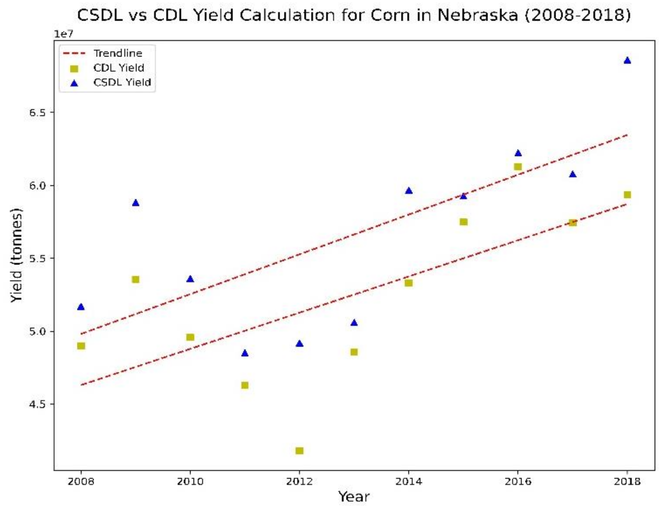


Figure 3.2: Comparison of yields calculated using CSDL against NASS yields.

and are thus expected to be accurate. However, there have been some past concerns about these estimates due to fears of hidden agendas at the agency, statistical biases, or large differences between quarter-to-quarter estimates (Good et al., 2011; Irwin et al., 2014). Despite these concerns, this dataset remains the best estimate of crop yield trends at large scales in the United States, especially due to the lack of publicly available, affordable, and large scale in-situ data (Deines et al., 2021).



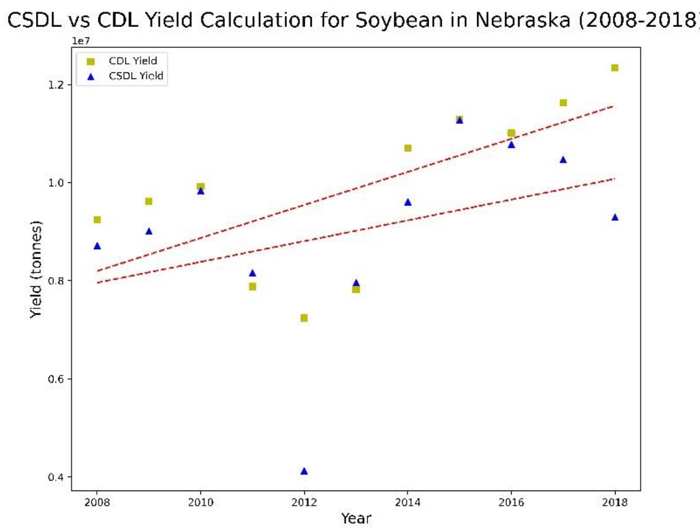


Figure 3.3: Comparison of yields calculated using CSDL and CDL (2008-2018).

The CSDL and CDL both have high R^2 with NASS acreage statistics from 2008 to 2018 (Wang et al., 2020). CDL yields have similar long-term trends as both CSDL and NASS for corn but does not suffer the same disagreements in 2012 and 2018 that CSDL does with NASS soybean yields (Figure 3.3). The agreement between CDL and NASS is expected, as the primary goal for the CDL since its inception has been to verify and improve NASS crop acreage estimates (Lark et al., 2017). On average, CSDL corn and soybean yield estimates were 7.28% higher and 9.57% lower, respectively, than CDL yield estimates from 2008 to 2018. The overall agreement between CSDL and CDL yield estimates and the CDL’s agreement with NASS county acreage estimates provide confidence in the CSDL hindcasting of corn and soybean observations.

3.2 Marginality by Criterion and Classification

Cropland in Nebraska shows relatively small amounts of marginality for productivity, with approximately 13% and 10% marginal for corn and soybean, respectively (Figure 3.5). Corn yield marginality is evenly spatially distributed, with marginality slightly increasing east to west across the state. This distribution is likely influenced by the spatial gradations of annual rainfall amounts, which decrease from east to west across Nebraska (A. Irmak et al., 2010). Soybean yield marginality shows more of a northeast to south central spatial distribution. Part of the differences in these distributions is the limited diaspora of soybean planting, with the CSDL showing limited to no planting of soybean in parts of western Nebraska during the study period. Soybean planting is limited in the western half of Nebraska as that geographic region is responsible for around 75% of wheat production and features rotation cycles that incorporate fallow periods to conserve water or crops such as corn or sunflowers (Hein & Kamble, 2003). This lack of soybean planting in western Nebraska is seen in the lack of markets that buy soybeans compared to corn and red winter wheat (Cusato-Wood, 2020). Gopalakrishnan et al. (2011) found 0.64 million ha of land produced less than 9 tonnes/ha and was marginal for grain (corn) yield. Their amount is less than what this study found (Table 3.1) and had a different spatial distribution, with a distribution across the center of the state (Gopalakrishnan et al., 2011, Fig. 1).

Heat stress had the highest levels of marginality for any criteria for corn, with 59% of cropland being affected, primarily across the southern half of the state (Figure

Table 3.1: Summary of marginality statistics by criteria marginality and marginality class.

	Corn		Soybean	
	% Cropland	**Area (ha)**	**% Cropland**	**Area (ha)**
Criteria Marginality				
Yield	13%	986,736	10%	786,927
Heat Stress	59%	4,487,184	11%	857,147
Root Zone Depth	5%	417,824	3%	230,378
Available Water Storage	15%	1,169,478	12%	928,698
Soil Organic Content	25%	1,926,026	24%	1,859,274
*Slope**		355,210	5%	
*Ponding**		74,498	1%	
*Droughty**		845,764	11%	
Marginality Class				
None	23%	1,788,123	56%	4,283,194
Low	63%	4,776,822	34%	2,597,867
Moderate	12%	902,813	10%	726,901
High	2%	178,775	0.5%	38,572

**Not crop-specific*

3.5). Soybean had much less cropland affected by heat stress, with around 11% of cropland area that was distributed primarily in the southwest and west of the state. While much of the southern half of the state is under long-term irrigation, areas exist in the extreme southeast, central southwest, and western Nebraska that are primarily rainfed (Figure A.1). These areas could experience increasingly negative impacts from heat stress due to increases in extreme air temperatures (dos Santos et al., 2022). While Nebraska has experienced an expansion in irrigated cropland, the increasing negative impacts from heat stress could potentially expand irrigated cropland in the areas noted above and put further stress on the underlying water supplies (Johnson et al., 2011). The connection between rainfed cropland that has been identified as experiencing heat stress and the impacts on future irrigation policy and management warrants additional study, especially for creating targeted irrigation policies in the future.

Root zone depth marginality was found on a relatively minor amount of cropland in Nebraska, around 5% and 3% for corn and soybean, respectively (Figure 3.5). Root zone depth marginality is found mostly in western, and along river systems throughout, Nebraska. Underlying soils in western Nebraska are characterized by exposed or shallow depths to bedrock, high levels of gravelly sand, and shallow loess or loamy soils underlaid by the bedrock and/or gravelly sand (Elder, 1969). All these factors can potentially constrain root development and impede water and nutrient uptake. As noted above, wheat has been the predominant agricultural crop in this area and was suggested as far back as 1969 (Elder, 1969; Hein & Kamble, 2003).

Available water storage marginally is spatially distributed similarly between corn and soybean across Nebraska and is found in around 15% and 13% of cropland respectively (Figure 3.5). Spatial patterns follow rivers and the associated floodplains in addition to western Nebraska. The soil characteristics of western Nebraska were discussed above and these combine to create soils that are incredibly well drained and have limited water storage capacity (Elder, 1969). Cropland found in rivers and floodplains in Nebraska contain soil parent materials of sand and silt, sand, or alluvium materials, which are characterized as incredibly well drained and limited in water storage capability (Elder, 1969). Droughty soils, which impact about 11% of all croplands, have

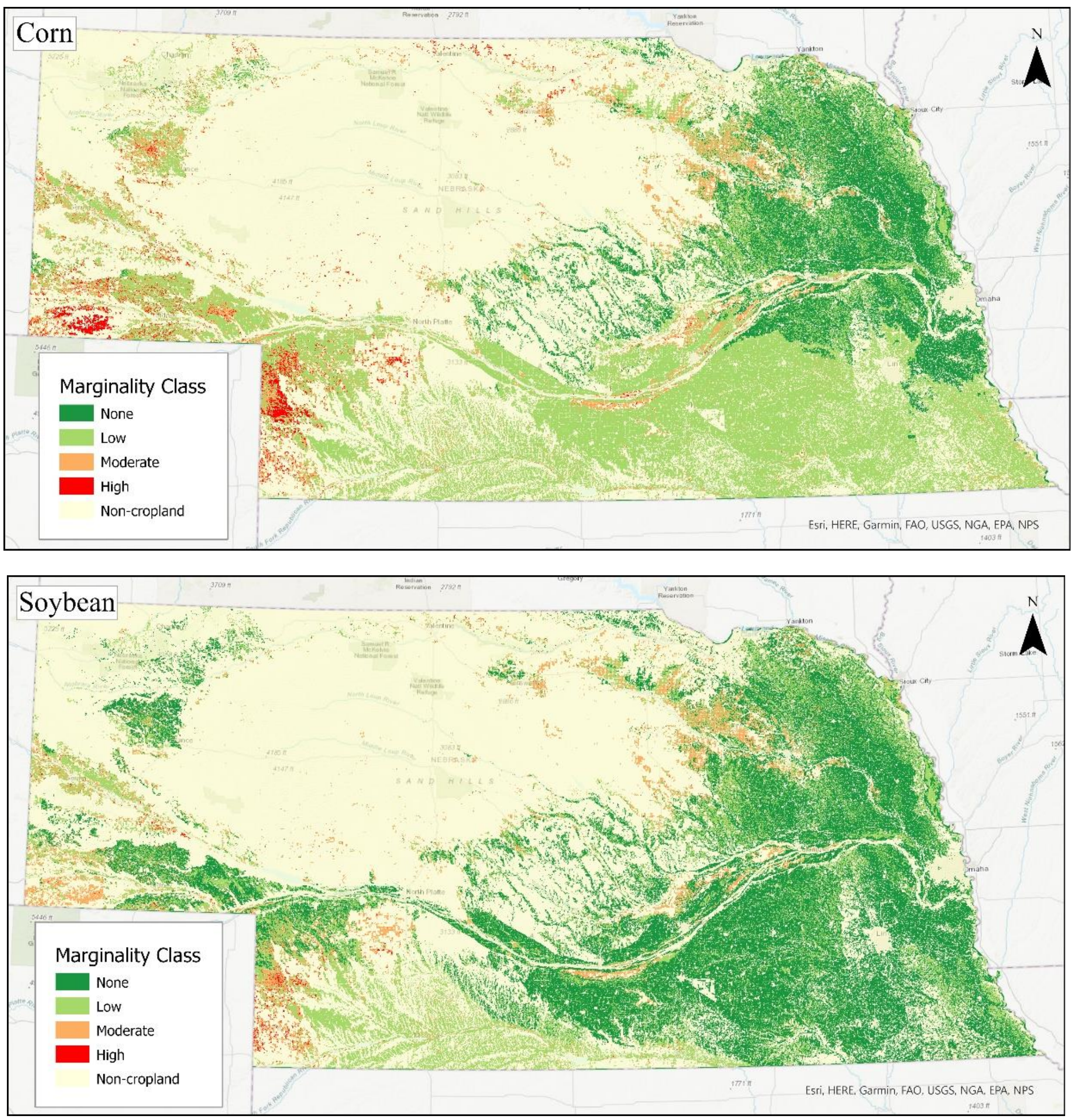


Figure 3.4: Marginal cropland classification.

similar spatial distributions as available water storage, likely due to available water storage being an input into droughty soil calculation (Soil Survey Staff, 2021).

Marginality for soil organic content has a broad spatial distribution across cropland in Nebraska (Figure 3.5). Localized patterns in the eastern half of Nebraska, outside of the Sandhills, are found along rivers, tributary streams, and drainages. Low SOC in western and southwestern Nebraska and the Sandhills are due to underlying soil qualities (Elder, 1969). The percentage of cropland marginal for soil organic content is less important than the spatial distinction as it was driven by the quantile classification and would be expected to be around 25%.

Slope and ponding marginalities are limited and occur on only 5% and 1% of Nebraska cropland (Figure 3.5). Slope marginality areas is similar to that found by Gopalakrishnan et al. (2011) at 350,000 ha but that study used 15° of slope across all land classes in Nebraska and were spatially distributed in the Sandhill region, making direct comparison between the studies difficult. While Gopalakrishnan et al. (2011) did not directly address ponding, they did examine soil characteristics that could lead to ponding including poorly drained soils, frequently flooded areas, and the intersection of both across all land classes (700,000 ha). The current study found ponding occurred on an area equivalent to about 10% of Gopalakrishnan et al.'s findings (74,498 ha), a likely indicator that crops are most likely not currently cultivated in most of areas identified by Gopalakrishnan et al. (2011) as poorly drained and/or frequently flooded.

Two marginality classification images, one apiece for corn and soybean, resulted from criteria inputted into the multi-criteria evaluation model (Figure 3.4). The largest differences between corn and soybean marginality were the percentage of cropland

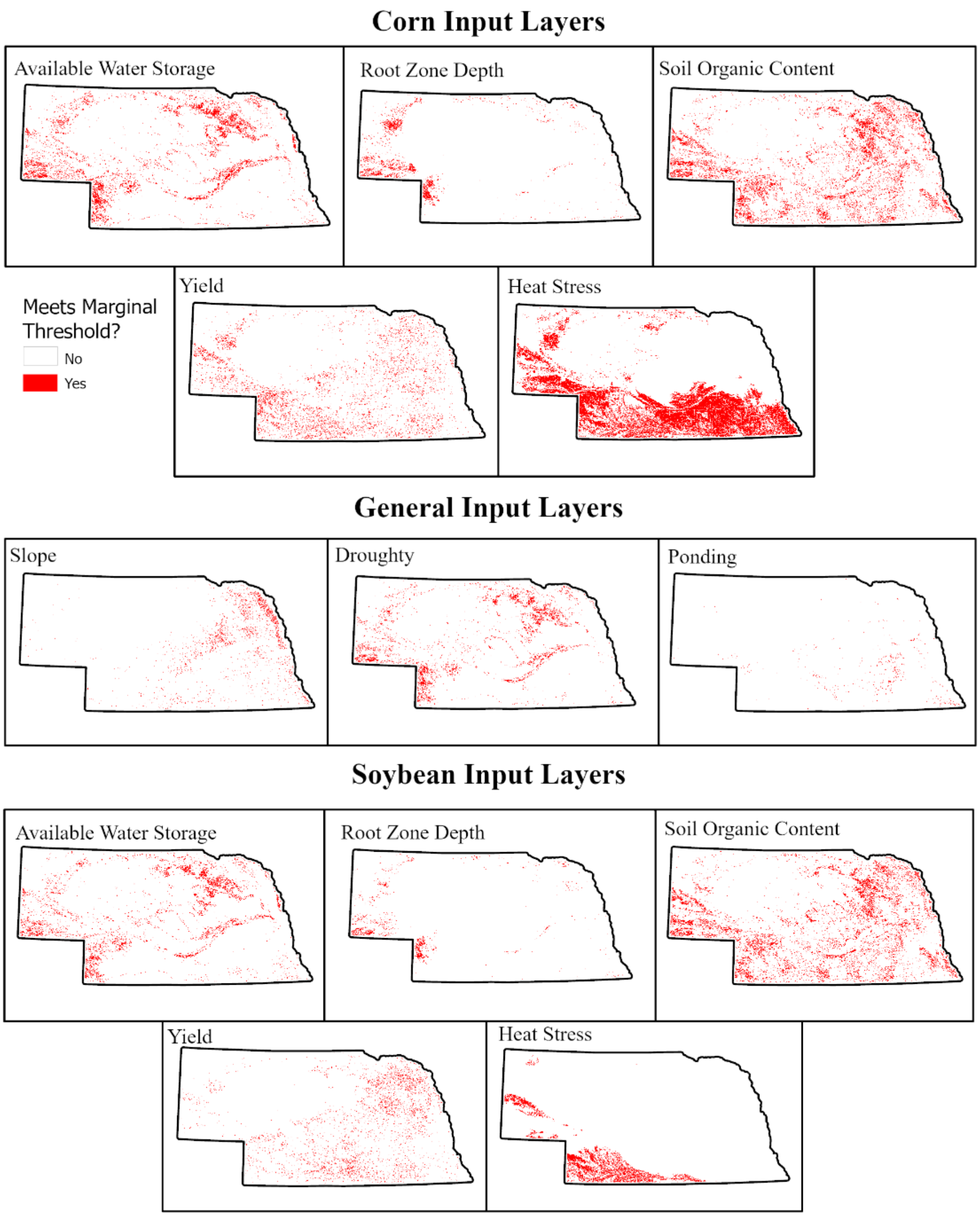


Figure 3.5: Final criteria input layers for MCE.

classified as non- or low marginality. Slightly less than a quarter of Nebraska croplands were found to be non-marginal for corn and just over half for soybean. The low marginality classification was the dominant classification by area for corn at 63% of cropland while being around half as much for soybean at 34%. Heat stress largely influences the low marginal classification in corn due to the large percentage of cropland area that it coincides with that other criterion do not. The moderate marginality class accounts for about 12% and 10% of cropland for corn and soybean, respectively. The high marginality class (5 or more criteria) occurs on a miniscule amount of cropland.

Spatially, corn marginality classification increases from the northeast to the southwest of Nebraska, with higher marginality classes in the northeast of Nebraska found in river drainage networks. Soybean marginality follows more of an east-west trend, with the highest marginality occurring in southwest Nebraska, like corn. Much of these trends are driven by the underlying soil properties, as soils make up five of the eight criteria, of which three soil criteria (root zone depth, available water storage, droughty) have similar spatial trends (Figure 3.5). This shows that these three factors could be represented in future work at other spatial extents through a single criterion such as soil type or category. The trends of increasing marginality are approximately the inverse of farmland, where prices tend to decrease from east to west across Nebraska (Jansen & Stokes, 2022).

3.3 Long-term Crop Rotation

The programmatic method of identifying long-term corn-soybean crop rotation shows it occurs primarily in eastern Nebraska on approximately 2.47 million hectares of cropland (Figure 3.6). This accounts for about one-third of all croplands in Nebraska and is evenly divided between irrigated and rainfed agriculture as defined by the *irrigation* mask (49% vs 51%).

Table 3.2: Percent of area by crop and crop rotation class.

Marginality Class	Corn		Soybean	
	Crop Rotation	Non-crop Rotation	Crop Rotation	Non-crop Rotation
None	39%	16%	71%	49%
Low	56%	65%	24%	39%
Moderate	5%	15%	4%	12%
High	0.15%	4%	0.03%	0.73%

Percent of within rotation-class cropland of non-marginality are much higher and percent cropland per marginality class lower under a long-term crop rotation, as seen in Table 3.2. The results are most striking for the moderate and high marginality classifications. Cropland not under LCR had 3 times more area than LCR cropland in the moderate marginality class for both crops. This jumps to almost 25 times more area in the high marginality class. While it is hard to say LCR directly decreases marginality due to the spatial heterogeneity of soil characteristics, climate factors, and cropping systems across such a large spatial extent, the net positive effects on marginality fit with the

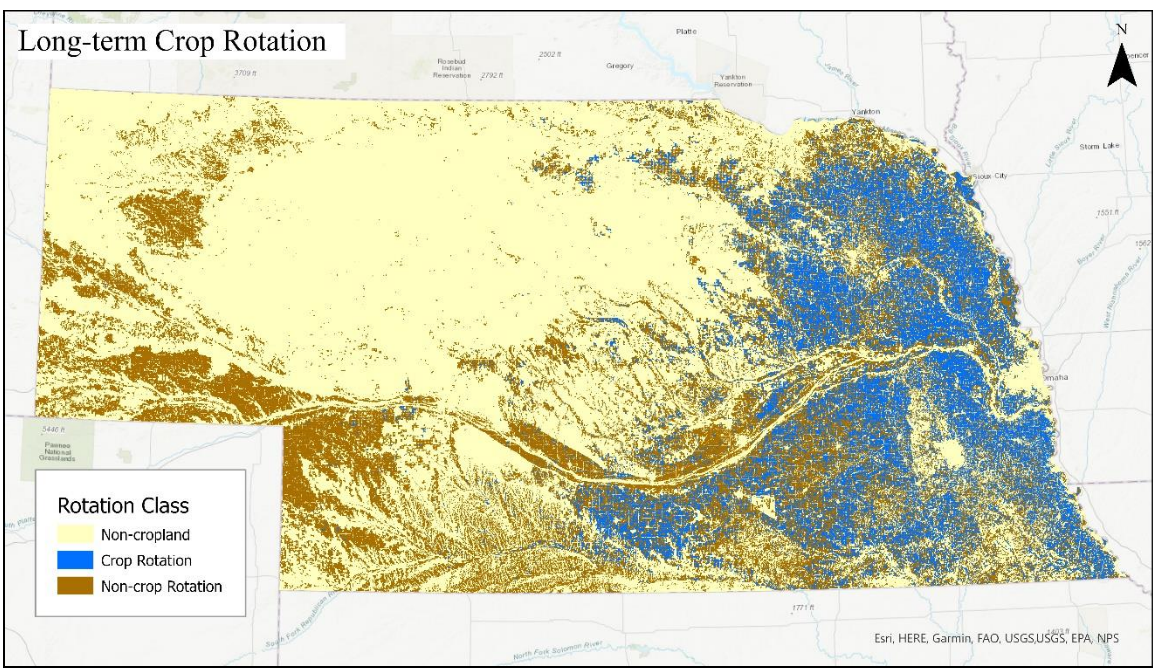


Figure 3.6: Long-term corn-soybean crop rotation in Nebraska (1999-2018).

previously stated benefits of crop rotations on individual criterion (Bowles et al., 2020; Bullock, 1992; Crookston et al., 1991). Therefore, if cropland drops out of LCR, it could face increased marginality and result in lower long-term yields.

While this method does use a quantification-based approach to identify LCR, it does not fully describe the rotations that are occurring at distinct time periods. In short, it does not allow for trend analysis and so would not be suitable for studies that required this. For studies that seek to identify crop rotation patterns, other studies have used multiple methods including string matching, raster calculators, and algorithmic approaches (add citation). Monoculture cropping has been increasing during the study period, especially on newly converted cropland, and could be occurring more recently on lands identified in this study as LCR (Long et al., 2014; Plourde et al., 2013; Rosenzweig & Schipanski, 2019; Sahajpal et al., 2014). Crop rotation identification would also be needed where agricultural cropping systems have not been well studied using methods in the literature. This is not an issue for Nebraska as its cropping systems are dominated by corn and soybean, with wheat and corn in the western reaches of the state. A potential addition to the methodology would be to observe whether temporal stacks identified as LCR had been converted to monocropping during recent years and drop those pixels from the crop rotation classification.

3.4 Example Sites

The example sites are useful for demonstrating local marginality classification patterns and the contributions of each criterion (Table 3.3) alongside irrigation and long-term crop rotation patterns (Figure 3.7). The Northeast site features marginal classifications of None to Moderate for both corn and soybean, with similar spatial

Table 3.3: Example site statistics.

	% of Site Area			% of Site Area							
Site	**Irrigated**	**Crop Rotation**	**Crop**	**Yield**	**Heat Stress**	**Root Zone Depth**	**Available Water Storage**	**Soil Organic Content**	**Slope**	**Ponding**	**Droughty**
Northeast	72%	42%	Corn	13%	0%	0%	53%	70%	0%	0%	53%
			Soybean	19%	0%	0%	54%	69%			
Southeast	0%	21%	Corn	1%	56%	7%	11%	0%	2%	9%	7%
			Soybean	2%	0%	3%	6%	0%			
Central	72%	29%	Corn	2%	85%	0%	54%	58%	4%	0%	51%
			Soybean	5%	0%	0%	54%	57%			
Southwest	65%	7%	Corn	16%	89%	46%	38%	24%	0%	1%	27%
			Soybean	15%	89%	18%	16%	16%			

patterns for both crops. These patterns are driven by yield, soil organic content, available water storage, and droughty marginality (Table 3.3). Yield marginality with almost twice the percent area for soybean when compared to total area of cropland across the state. The site is also heavily irrigated (72%) and when combined with low water storage capacities and low soil organic content, this site would be a prime candidate for conservation practices aimed at improving physical soil characteristics and soil health. One of these practices could be increased use of crop rotations, as some of the fields with lots of Low and Moderate marginality classes were not classified as LCR.

The Southeast site generally contains soybean marginality that is one marginal classification less severe than corn marginality i.e., Low rather than Moderate (Figure 3.7). This is likely due to the cropland in the area experiencing heat stress marginality for corn while none exists for soybean (Table 3.3). The heat stress as well as lack of irrigation and relatively minimal amount of yield marginality would suggest that this site receives adequate rainfall to meet water needs for corn at this time. The Southeast site has the highest amount of ponding of any site (9%), low amounts of available water storage and droughty soils and no marginality for soil organic content, all of which adds to the narrative that this region receives adequate rainfall for crop planting. However, concern for future climate change could push this site into adopting more irrigation, something to be considered for water management in the region.

The Central site features Low to High marginality classes for corn and all classes for soybean. The most severe marginality occurs in a band across the upper two-thirds of the site (Figure 3.7), where underlying riverine soils contribute to high amounts of available water storage, soil organic content, and droughty marginality (Table 3.3). This

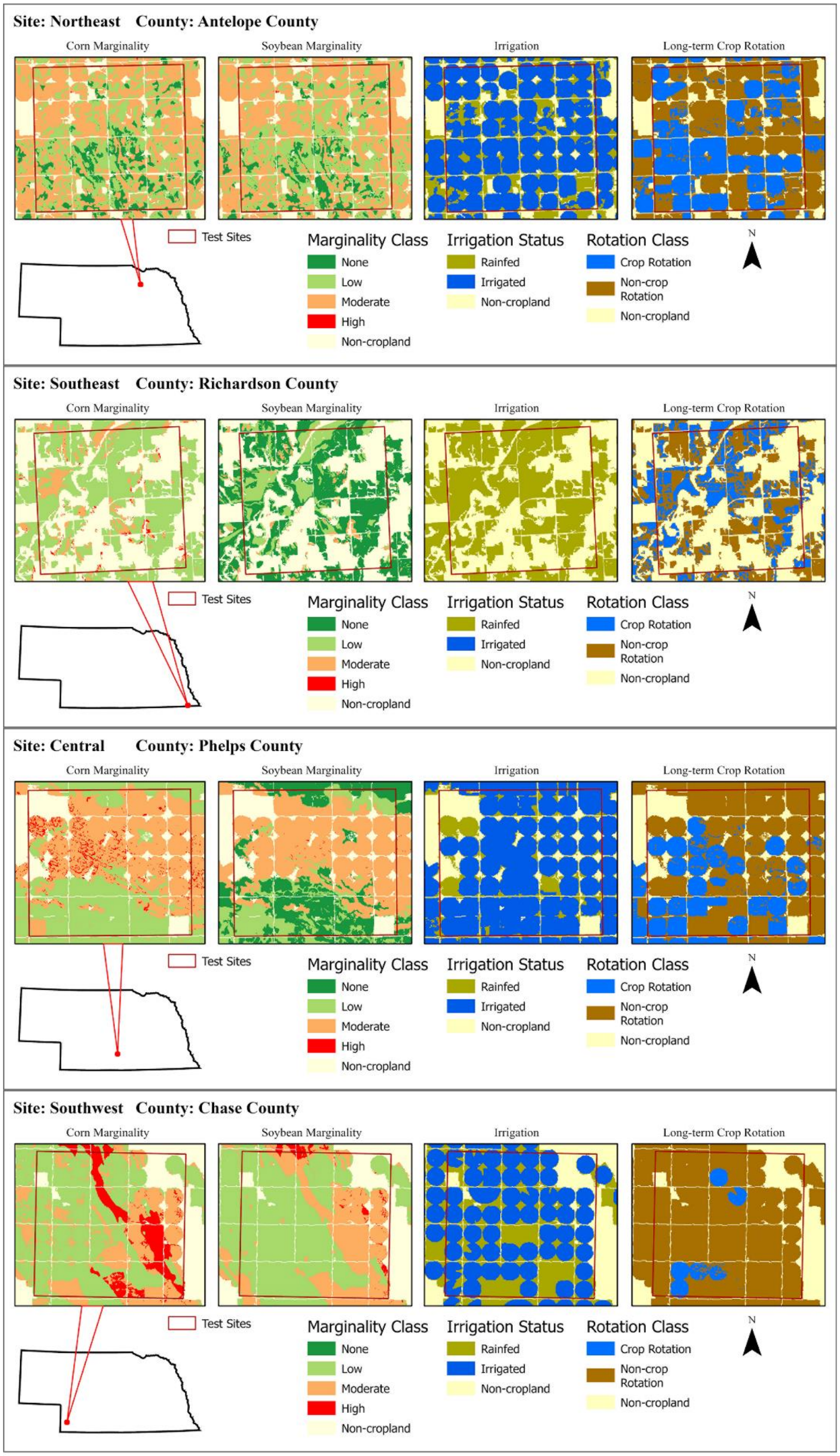


Figure 3.7: Maps of example sites in Nebraska.

site is a heavily irrigated area (72%) but has low yield marginality, which could be an indicator that the quantity of water may be higher in this area to offset any yield issues caused by the underlying soil. For corn, the Central site features a heavy concentration of heat stress marginality. Crop rotations could also be adopted more in this area, as only a limited amount of the cropland in the upper two-thirds of the site has been under a crop rotation.

The Southwest site features the greatest amounts of the High marginality class of all the sites. This is also representative of the area, as marginality was highest for corn and soybean in the west and southwest of Nebraska. The Southwest site has some of the most yield marginality, is the only site with heat stress marginality for both crops, and the most impaired root zones (Table 3.3). High marginality classification for corn is most prominent in the eastern half of the site where soybean marginality is Moderate (Figure 3.7). This is likely due to corn having more than twice the amount of marginality across the site for root zone depth and available water storage with a more than half again amount of soil organic carbon marginality (Table 3.3). Irrigation is present on much of the site while crop rotation is not. The latter is likely driven by a lack of planting of soybean in the area (see Section 3.2 for more details).

CHAPTER 4: CONCLUSION

This study aimed to answer several research questions with regard to marginal cropland in the state of Nebraska. First, this study sought to identify and classify marginal cropland for corn and soybean. Based on the results of the multicriteria evaluation, marginal cropland was identified across Nebraska and generally increased from the northeast to southwest. Second, this study set out to determine where cropland was under a long-term corn and soybean crop rotation and identify its impacts on marginality classification in Nebraska. A long-term crop rotation had positive effects on reducing marginality, especially more severe classifications, and highlights the importance of this cropping practice. Furthermore, the results can inform policymakers, researchers, and outreach professionals where cropland has the greatest potential for uses with regards to biofuel production, conservation, and/or solar energy development. Finally, the methodology is easily replicable yet robust, and allows for transference to other spatial extents and scales with localized threshold updating.

While the thresholds for individual criterion were set to match the biotic and abiotic conditions of Nebraska, the quantile approach to thresholding some criterion allows the application of this model to other spatial extents and scales with minimal changes. While the importance of soil health and structure is undeniable, soil characteristics became the most weighted group of criteria, especially when the effects of precipitation were found to be non-existent. This limitation could be overcome in future work by excluding one of the two soil water criteria based on relevance to the study area or using a drop-out when the results are similar, so their effect is only applied once in the MCE. Another limitation was inherent in the secondary data that was used being predominantly products derived from satellite imagery. Products derived from satellite imagery can contain errors such as cloud interference, speckled classification, and misalignments between pixels and field boundaries, to name a few. Despite these limitations, the overall model shows much promise for informing decisions regarding policy and practice from the state to field-level. Additionally, field-level advice for farmers should always be constructed with in-situ testing as needed and farmer insights about local conditions, regardless of the findings of ex situ research.

Based on these findings, there are opportunities for collaboration between researchers and outreach professionals. There exists a continued need for researchers to understand the drivers and motivations of farmers' land management decisions and for outreach professionals to integrate these findings into their conversations with farmers, especially around conservation, biofuel production, and solar energy capture. By integrating the human dynamics of agricultural practices with marginal land classification, outreach professionals would be able to prioritize cropland for outreach of best management practices, program money, and other improvements to the long-term sustainability of agriculture in Nebraska. A great starting point about barriers and motivations for outreach professionals around conservation, with potential insights into biofuels production and solar energy capture, is Ranjan et al., 2019.

Locating cropland under a long-term crop rotation provides an opportunity for University of Nebraska Extension outreach to farmers about the benefits of adding winter wheat to the corn-soybean crop rotation in Nebraska. This practice has shown promise in Illinois and while it would need to match the farmers existing business plans and logistical capabilities, support from Extension personnel and potential conservation payments from USDA could help offset these challenges. Furthermore, Extension researchers could benefit from the opportunity to study and examine the impacts of adding winter wheat to the corn-soybean crop rotation in Nebraska. Such impacts that could warrant study include changes in soil health, how and why farmers make land management decisions, and changes to economic well-being.

Opportunities for future work on improving and expanding this methodology also exist. The first, mentioned above, will be to limit the effects on marginal classification by cooccurrences of soils limited available water storage and droughty soils by giving these overlaps the weight of a single criterion rather than two criteria. Second, mentioned briefly in section 3.3, will be changes aimed at improving the value-added properties of identifying long-term crop rotation with better informing about current cropping systems. Third, a sensitivity analysis of soil organic content marginality between the derived SOC_{score} and other SOC measurements will be conducted to test and validate SOC_{score} further. Finally, there are additional criteria that will be considered for addition to the MCEs. One of those will be using nutrient runoff maps, in particular the proximity of vulnerable cropland to rivers and other water sources with high nitrogen or other nutrient levels. Another will be examining if a spatial metric can capture important social, socioeconomic, or management considerations by farmers on cropland.

This research contributes much to the subject of marginal cropland classification. The described methodology bridges gaps in resolution, land class constraints, complexity, and scalability. While replicable and adaptable to a broad spectrum of criteria, the criteria examined provide a robust measurement of marginality as it exists on Nebraska cropland. In particular, the measurement of importance of different soil depths for soil organic content provides new insights on examining SOC through the root zone of a crop. The mapping of heat stress on plant health provides warrants serious considerations for future irrigation and agricultural systems as they exist now and evolve in the face of climate change. Finally, the novel method for long-term crop rotation identification expands crop-rotation examination beyond previous temporal ranges and provides valuable insights into applications on marginal cropland in Nebraska.

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APPENDIX A: ADDITIONAL FIGURES

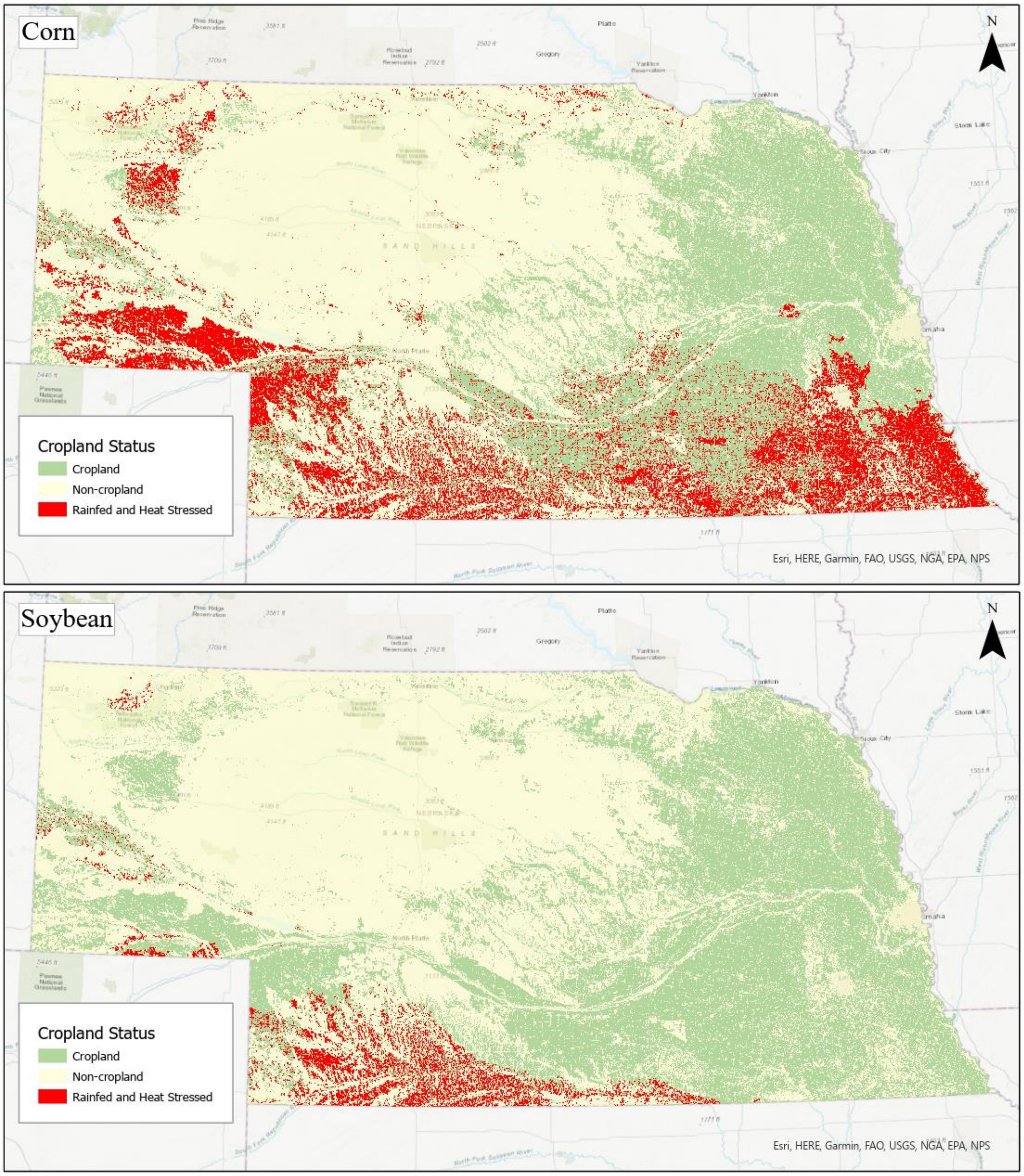

Figure A.1: Heat stressed and rainfed cropland by crop.

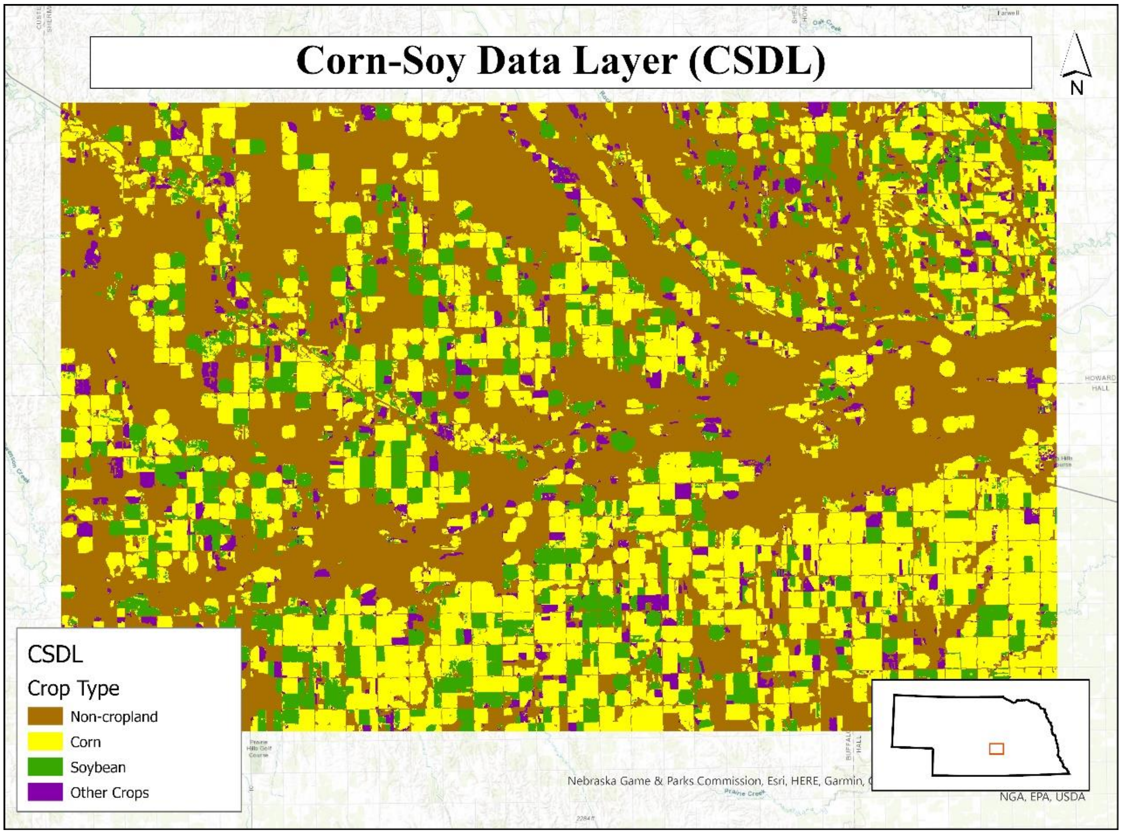

Figure A.2: Example of CSDL dataset.

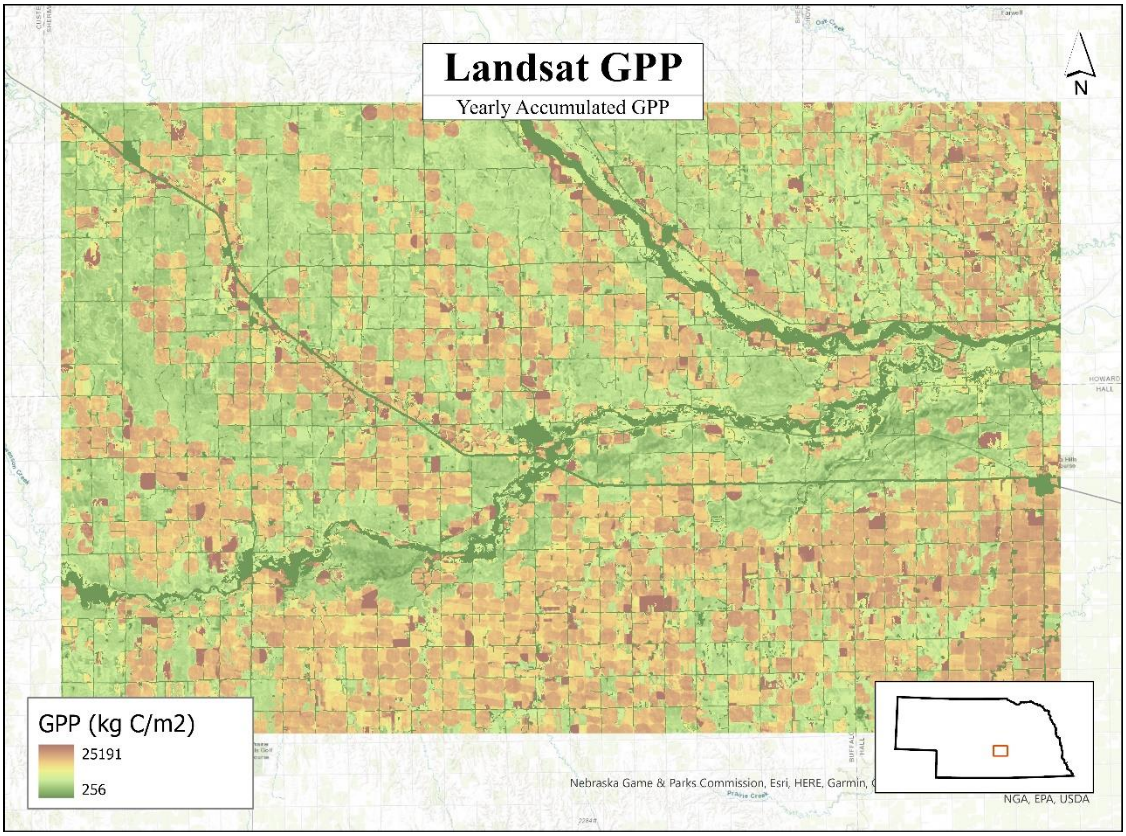

Figure A.3: Example of Landsat GPP dataset.

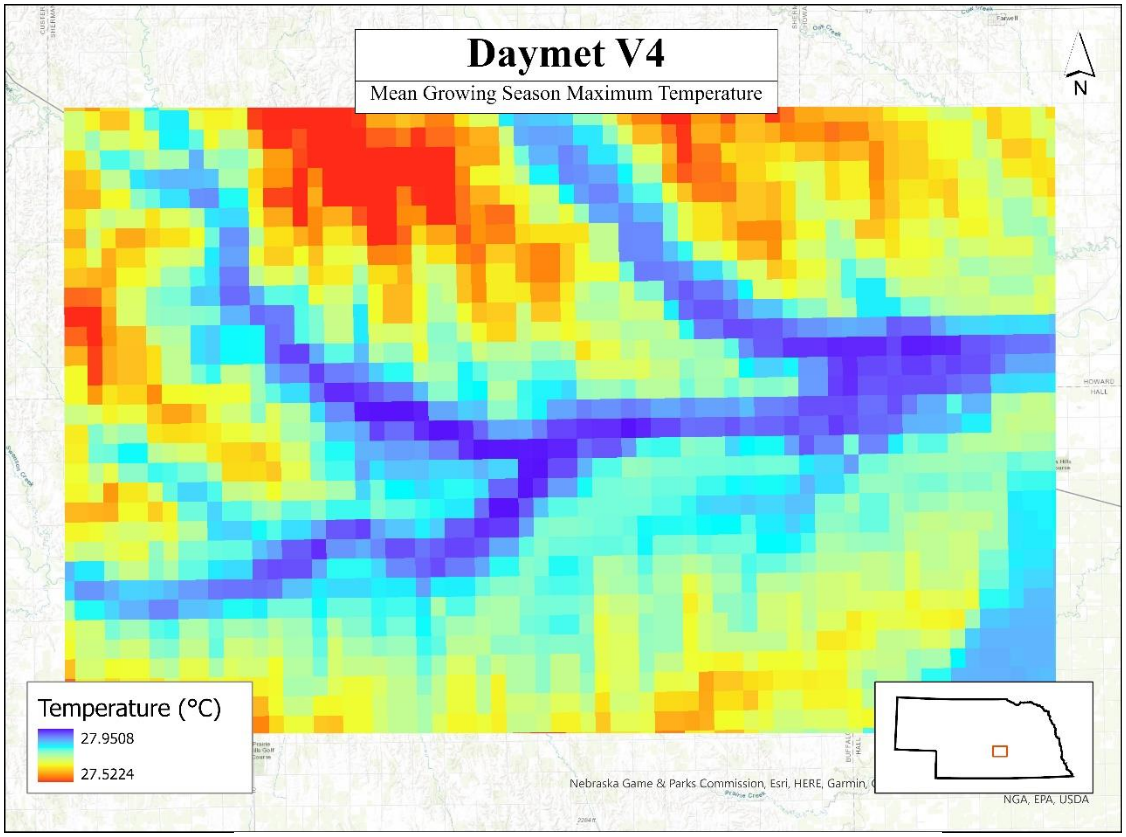

Figure A.4: Example of Daymet V4 dataset.

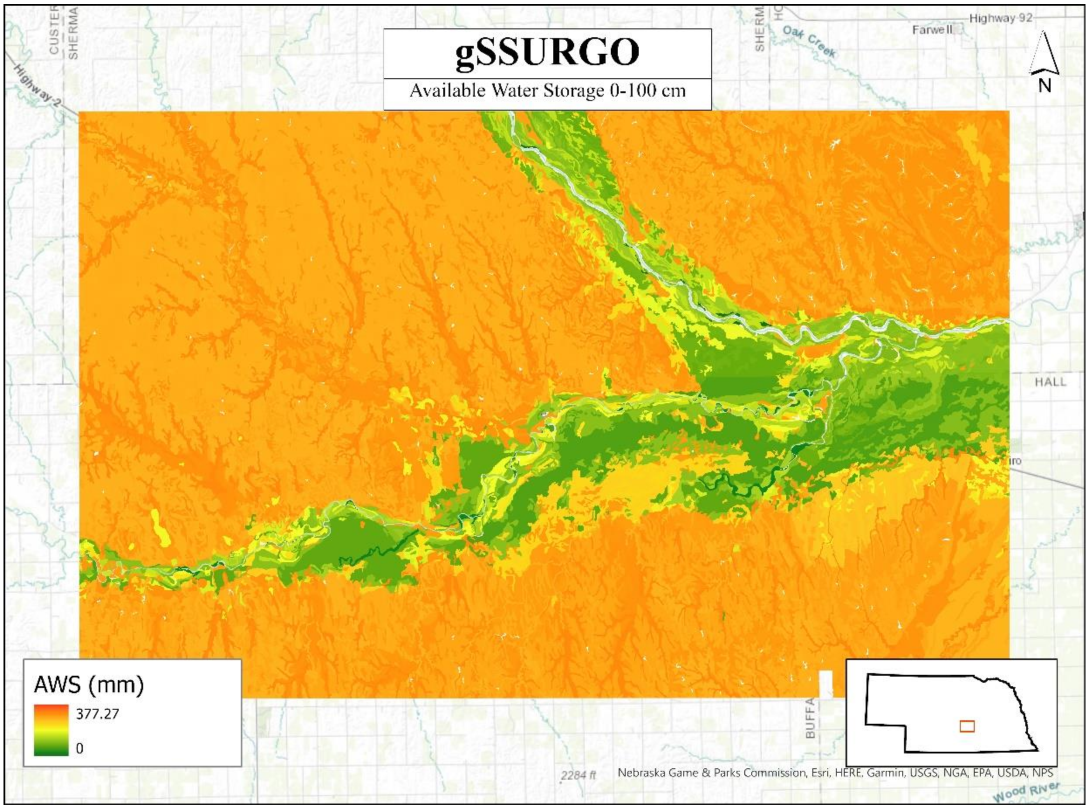

Figure A.5: Example of gSSURGO dataset.

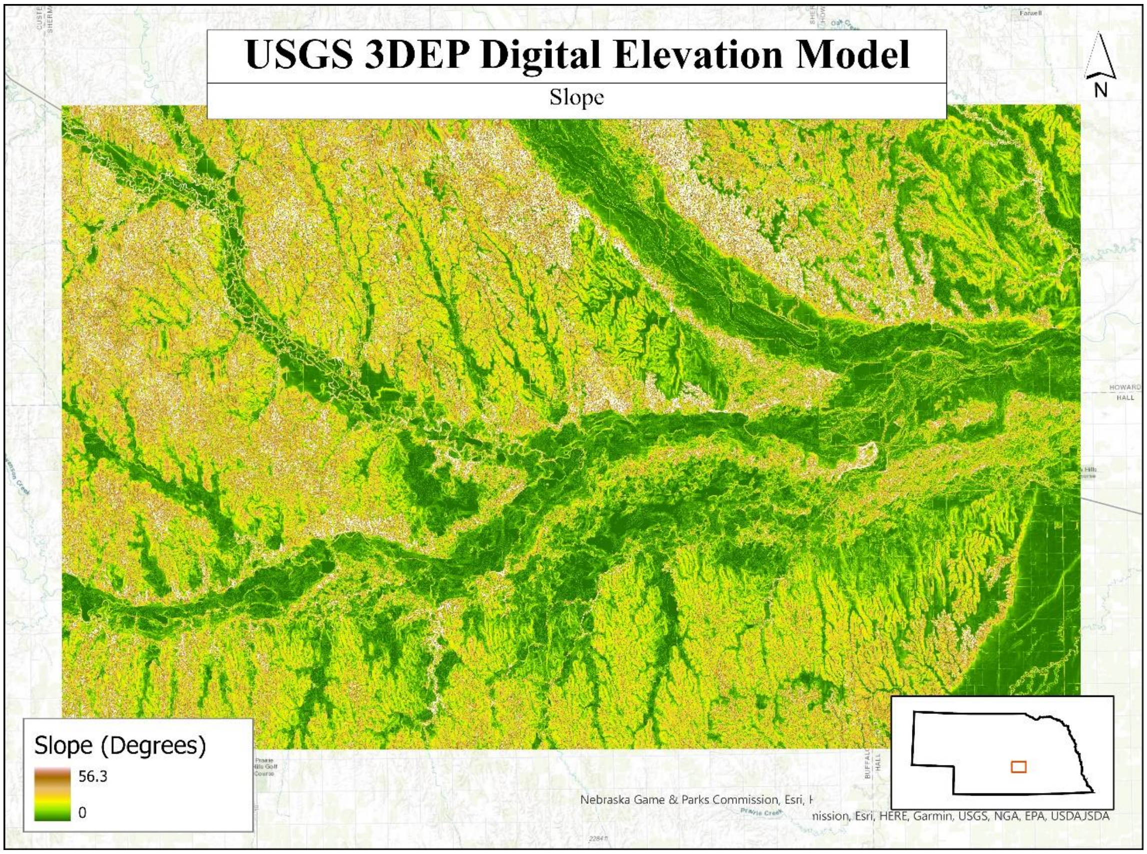

Figure A.6: Example of USGS 3DEP DEM dataset.