A Multi-Criteria Land Suitability Assessment of Field Allocation Decisions for switchgrass

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With the goal of evaluating biomass resource availability in certain regions in the US, the US Department of Energy, U.S. Department of Agriculture, US Environmental Protection Agency, national laboratories, and U.S. Forest Service research laboratories, together with academic and industry collaborators, performed a resource analysis study, *2016 Billion-Ton Report: Advancing Domestic Resources for a Thriving Bioeconomy, Volume 1: Economic Availability of Feedstocks,* using POLYSYS model to estimate biomass potential in the US. The study provided county- and state-level biomass potential projections, with biomass feedstock production estimates and suitability assessment of lands acreage likely to transition to energy crops. For this analysis, we estimate biomass supply by year 2028, more specifically, lands acreage transition to switchgrass in the Midwest of the US, across 50 counties in 3 states (Nebraska, Kansas, and Colorado). We propose a multi-criteria site suitability framework, to determine the potential acreage and production for switchgrass, at the field level. Site selection criteria span agronomic and ecosystem services such as previous land cover, crop rotation, soil water holding capacity, crop productivity, field efficiency, topography, soil organic matter, soil leaching propensity, distance to surface water bodies, and soil erosivity. Efficient agricultural field selection for dedicated energy crops field allocation is critical to evaluate biomass resource availability, and it is our position that estimation at the field level would provide a more accurate and useful estimation to support an emerging bioeconomy. Using field suitability scores and county-level assessments, we model land allocation decision for energy crop in the future, estimating the spatial distribution of dynamics of energy crop adoption with priority to fields scoring the highest. Compared with POLYSYS results from the report mentioned above, our method shows good performance overall, with about 2% and 1.2% of difference in switchgrass acreage allocation and crop production, respectively.

Keywords: *Land suitability assessment; Bioenergy; Switchgrass; Multi-criteria decision making; Integrated landscape management*

1. Introduction

Developing sustainable and low-cost biomass production strategy is vital to increase energy security, energy independence, and environmental stewardship (Langholtz et al., 2016). As the largest single source of renewable energy representing 3.9 quadrillion of 9.6 quadrillion British thermal units (Btu) in 2015 (EIA, 2016), sustainable biomass production is critical to long-term viability and development of technology for green energy. Langholtz et al. (2016) and Efroymson et al. (2017) investigated actions and strategies that could enhance the environmental and economic benefits while minimizing negative impacts of biomass production. Under various land-use change scenarios, their research provided county-level estimates of potential future biomass availability. Their analysis looks at low- and a high-yield (annual improvements in crop yield for commodity crops and energy crops) scenario, and near- and long-term estimates of biomass potential. Energy crops such as miscanthus, energy sorghum, switchgrass and perennial woody crops can produce high biomass yield with low or minimum nutrient and water inputs (Heaton et al., 2008; Kiniry et al., 2013; Knoll et al., 2011). Converting crop land to bioenergy crops can reduce tillage and soil disturbance, reduce fertilizer applications, and change harvesting management regimes. Such conversion requires planning, consisting in developing medium- to long-term agricultural practice strategies to help guide the future of energy crop production. One way to perform this planning is to use advanced modelling techniques, capable of estimating bioenergy potential in the future.

Land-use planning techniques are utilized to identify the most suitable fields to achieve optimized economic and environmental benefits. Land suitability analysis (LSA) is a method of land evaluation, identifying limiting factors for planting a particular crop and ultimately estimating the supply potential for this particular crop (Steiner et al., 2000). LSA evaluates the capabilities and potential of land for different objectives based on multiple criterion and constraints, which may often be conflicting. Multi-criteria decision making (MCDM) approaches enable a logical and consistent decision while considering these criteria (Berbel et al., 2018; Solangi et al., 2020). Geographic information systems (GIS) as reported by several recent studies' results have a great potential to improve land suitability evaluation (Ostovari et al., 2019; Tercan and Dereli, 2020). Integrated with GIS techniques, MCDM techniques have been applied in different studies for land-use decision support (Heaton et al., 2008; Kiniry et al., 2013; Knoll et al., 2011). GIS-based multicriteria LSA has been widely adopted to assess and select suitable fields that meet certain land-use requirements (El Baroudy, 2016; Hoseini and Kamrani, 2018; Qiu et al., 2017).

Based on different land-use requirements, many different weighting techniques and methods have been developed for LSA studies. According to Malczewski (2006)'s review, combination rules technique include mainly Boolean overlay operations (Riad et al., 2011), weighted linear combination (WLC) (Ghosh and Lepcha, 2019; Malczewski, 2000), AHP (Analytical Hierarchy Process) (Bozdağ et al., 2016; Malczewski, 2000), Outranking methods like ELECTRE (elimination and choice translating reality) or PROMETHEE (preference ranking organization method for enrichment evaluation) (Pohekar and Ramachandran, 2004) and TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) (Mukherjee et al., 2018; Ramya and Devadas, 2019). For our research, we find WLC the most adequate. Our choice is based on the fact that, as opposed to AHP and outranking methods, there is no requirement for criteria preference or ranking, which may vary across end users or stakeholders. We also employ, in complementarity with WLC, the Boolean method. This approach combines each criterion with binary logical operations, while the WLC method aggregates continuous or discrete values for each criterion (Romano et al., 2015). However, the value determined by the WLC method is usually a quantitative and crisp value, which cannot catch the uncertainty and imprecision involved in the evaluation process. One way to address this issue is the use of fuzzy rule-based theory, which has been implemented in several studies (Özkan et al., 2020; Reshmidevi et al., 2009; Tashayo et al., 2020). Instead of a point value, the fuzzy membership function can capture more information by capturing the partial membership between 0 and 1, via a standardization procedure.

Integrated Landscape Management (ILM) has emerged in recent years as a strategy to integrate biomass production practices into agricultural production fields via sustainable crop residue harvest and collection and dedicated energy crop cultivation in subfield areas. By converting non-profitable subfields to energy crops, production has been demonstrated to improve annual biomass availability, soil carbon sequestration, and preserve soil nutrients (Follett et al., 2012). Several modeling efforts have been used to confirm the efficiencies gained using ILM techniques, including production cost reduction (Roni et al., 2020), field design profitability (Nair et al., 2017) and optimal field operation efficiency (Griffel et al., 2020; Toba et al., 2020).

LSA in this research focuses on the supply potential for energy crops on surplus land and opportunities for future land development. Several studies have assessed suitability for energy crop production across various places, with study areas in China (Liu et al., 2021; Xu and Zhang, 2013; Zhuang et al., 2011), EU (Hellmann and Verburg, 2011; Krasuska et al., 2010), Colombia (Younis et al., 2021), Ethiopia (Kahsay et al., 2018), Italy (Fiorese and Guariso, 2010; Pulighe et al., 2016), Canada (Joss et al., 2008), among others. LSA for potential land for energy crops has also been in the US to quantify the potential of biomass resources. Graham (1994) analysis identified and evaluated the lands in the US, Northeast, North Central, Southeast, South Central and Pacific Coast, that could support biomass crops and the amount of biomass that could be produced on those lands. Saha and Eckelman (2015) estimated bioenergy potential production on urban marginal lands of the city of Boston. Feng et al. (2017) assessed the suitability of marginal lands in Upper Mississippi River Basin (UMRB) for three promising bio feedstock crops, switchgrass, Miscanthus and hybrid poplar.

Unlike these studies that estimate land suitability at city, county or regional levels, our LSA provides assessment at the field level, and ultimately refine the BT16 (US DOE 2016 Billion-Ton Report) land estimates performed at county level (Langholtz et al., 2016). To the best of our knowledge, this study is the first-of-its-kind that provides means to estimate land allocation for energy crops at the field level, for a more precise estimation of bioenergy potential. In this land suitability analysis, we developed a geospatial multicriteria approach using a linear fuzzy-logic model and a site suitability scoring method, to select the most suitable fields to apply ILM strategy. This research aims at identifying land availability and performing land allocation for dedicated energy crops, switchgrass in this case, while offering long-term profitability for farmers and minimizing competition with commodity crops. The results produced from this LSA can be used to examine the feasibility of bioenergy feedstock development, and more importantly, to demonstrate benefits of ILM designs in optimizing ecosystem services and carbon management while meeting cost targets.

The rest of the paper is structured as follow: section 2 details the land suitability criteria developed, section 3 describes the site suitability selection approach, section 4 explains our methodology, section 5 presents results, and section 6 provides conclusions.

2. Criteria included in the ILM land suitability analysis.

Defining the right/adequate criteria for land allocation decisions for dedicated energy crops is critical. In our study, we identify and consider factors impacting the feasibility of integrating bioenergy crops production within midwestern agricultural fields. Past research identified several factors, including land cover or land use (Kamkar et al., 2014; Sarkar et al., 2014), soil physical characteristics (e.g. pH, fertility, texture, erosivity) (Braimoh et al., 2004; Dadhich et al., 2017; Machfudd, 2016), soil organic carbon/matter content (Schiefer et al., 2016), distance to water bodies (Houlahan, 2004), soil water holding capacity (Zolekar and Bhagat, 2015), and landscape features (e.g. slope, elevation) (Seyedmohammadi et al., 2016; Yi and Wang, 2013). In addition, the efficiency of farming operations may impact the feasibility of integrating bioenergy crops production within single agricultural fields. Machinery operation efficiency varies depending on factors such as field shape and size (Xangsayasane et al., 2019). For instance, non-convex or irregular field shapes can create issues and difficulties for equipment movement (Toba et al., 2020). Efficient landscape designs are thus pivotal to optimize ecosystem services and reduce costs in perennial agricultural systems (Poncet et al., 2016). Another criterion related to field operability is slope. There are varying suitable slope ranges for producing each crop, generally fields with slope steeper than 30 percent (16.7 degrees) is categorized as non-suitable land for crop cultivation and machine operations (Murphy et al., 1985; Tesfay et al., 2017). Based on these observations and studies, we consider the following criteria and document the data sources.

2.1. Land cover/crop rotation

The intensification of farming practices has caused many negative impacts on ecosystems such as soil erosion, soil carbon loss, water pollution and decreased pollinator habitats (Brittain and Potts, 2011; Cosentino et al., 2015; Nocentini et al., 2015). Crop rotations are determined from the USDA Cropland Data Layers[1] (CDL) at a 30-meter spatial resolution and are assigned to fields that are delineated based on 2008 Common Land Unit[2] (CLU) spatial field boundary data to determine crop rotations for each field. For this analysis, only fields under typical agricultural land use (maize, soybeans, winter wheat, and fallow rotations) are identified as suitable.

2.2. National Commodity Crop Productivity Index (NCCPI)

NCCPI was developed by USDA and is an index that combines soil physical, chemical and biological properties. It is employed to estimate commodity crop (i.e., corns, soybeans, cotton, or small grains) productivity in non-irrigated agricultural land and indicates the ability of soils, landscapes, and climates to foster crop productivity (Dobos et al., 2008). The NCCPI values are demonstrated to effectively predict corn and soybean yield in the non-irrigated land (Egli and Hatfield, 2014a, b). Values used in this paper are gathered from the NASS soil survey database[3].

2.3. Soil available water storage (AWS) within rootzone

Crop yield is highly related to soil available water, especially in non-irrigated and highly eroded agricultural lands (Arriaga and Lowery, 2003; Holzman et al., 2014). As an important soil physical characteristic to optimize crop production, soil water storage has largely been included in many land suitability assessment studies (Akıncı et al., 2013; Perveen et al., 2007). For this

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[1] Research and Science: CropScape and Cropland Data Layer - National Download. https://www.nass.usda.gov/Research_and_Science/Cropland/Release/
[2] Common Land Unit (CLU) https://www.fsa.usda.gov/Internet/FSA_File/clu__infosheet_2012.pdf
[3] Natural Resources Conservation Service https://www.nrcs.usda.gov/wps/portal/nrcs/main/soils/survey/

analysis, AWS data used is from the Soil Survey Geographic Database[4] (SSURGO), for soil depth of 0 to 0.3 m.

2.4. Field efficiency (FE)

Field efficiency implies the completion of a given agricultural field operation while wasting the least amount of time, and resources. Efficient landscape designs are thus key to reduce costs in perennial agricultural systems (Poncet et al., 2016). Griffel et al. (2020) research reveal a relationship between field shape, field size and harvesting efficiency in energy crops plantation. The results show that natural log transformation of the perimeter-to-area (P/A) ratio is the most efficient predictor for FE, with $R^2 = 71\%$, among shape descriptors. The specific equation to quantify field efficiency identified in the regression analysis is shown below:

$$FE_i = \beta_0 + \beta_1 . ln\left(\frac{P_i}{A_i}\right) \text{ Eq (1)}$$

where FE is the field efficiency for field i, β_0 is 0.179, β_1 is -0.145 and ln(P/A) represents the natural log transformation of the field boundary perimeter-to-area ratio for field i. For this analysis, the FE will be calculated for each field.

2.5. Topography (slope)

There are varying suitable slope ranges for producing each crop. Normally, slope between 5-15 degree is considered as moderate and less than 5 degree is considered as flat (Elsheikh et al., 2013; Kumar and Jhariya, 2015). Fields with slope steeper than 30 percent (16.7 degrees) are categorized as non-suitable land for crop cultivation and machine operations (Murphy et al., 1985; Tesfay et al., 2017). Therefore, lands with slope exceeding 16.7 degrees are excluded on the assumption that biomass cultivation, harvest, and collection activities cannot be effectively conducted on steep terrain without additional costs. Planting bioenergy crops such as switchgrass is expected to reduce soil disturbance and is less impacted by steep slope as it requires no-till seeding. In this analysis, areas with steeper slope (< 16.7 degrees) are classified as more suitable land for applying ILM strategy. United States Geological Survey's (USGS) National Elevation Data[5] (NED) data with a spatial resolution of approximately 10 meters are used to develop the slope data.

2.6. Soil organic carbon (SOC) storage

Soil organic carbon in the surface (0-30 cm) layer is essential for crops as it maintains water holding capacity and micronutrient cations (Al-Kaisi et al., 2005; Mustafa et al., 2011). Increasing soil organic carbon stock is a major benefit derived from converting crop land to energy crop production (Follett et al., 2012; Harris et al., 2015; Nocentini et al., 2015). SOC values at a field level are extracted from SSURGO[4] data.

2.7. Soil water leaching index (LI)

Intensive farming practices such as fertilizer and pesticide applications can cause environmental problems such as soil nitrate leaching and groundwater contamination. To estimate

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[4] Natural Resources Conservation Service Soils: Description of SSURGO Database https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/?cid=nrcs142p2_053627

[5] USGS National Elevation Dataset (NED). https://catalog.data.gov/dataset/usgs-national-elevation-dataset-ned

the potential of soil nitrate leaching, LI was developed by USDA (NRCS, 2013), based on soil hydrologic grouping and annual and seasonal precipitation. The index provides estimates of potential NO_3-N losses tied to agricultural management practices and has been used by researchers, growers, and policymakers as a decision support system. LI is calculated using precipitation data available from the PRISM Climate Group[6] at Oregon State University. The following equation is used:

$$LI = PI * SI \qquad \text{Eq (2)}$$

where PI is the percolation index and SI the seasonal index (Williams and Kissel, 1991).

2.8. Distance to water bodies.

In addition to soil properties, land cover is also impacting stream water quality. Tran et al. (2010) reported relationships between land-use types and stream water quality within 200-m distance. Houlahan (2004) results show that that the relationship between water quality and land-use becomes weaker at distances greater than 3000 meters. For the purposes of this analysis, scoring is based on a field-to-stream distance range of 0 to 3,000 m, following the equation below:

$$f = \begin{cases} 1: & 0 \leq x_s \leq 200 \\ \frac{(x_s - 200)}{3000 - 200}: & 200 < x_s < 3000 \\ 0: & 3000 \leq x_s \end{cases} \qquad \text{Eq (3)}$$

Where *x* is the is the value for the distance, *f* is the fuzzy function to capture distance to water bodies. We assume fields within 200m receive the highest score (1). From 200 m to 3,000 m, fields are ranked using a linear function. The score of 0 will be assigned for distance greater than 3000m. The spatial stream data was derived from the USGS National Hydrography Dataset[7] (NHD) which provided spatial and tabular information for rivers, streams, lakes, ponds, and other hydrological features within the U.S.

2.9. Soil erodibility factor (K factor)

Soil erosion is mainly caused by inappropriate soil management and has long been recognized as a major environmental threat to the productivity and sustainability in agricultural production systems (Cosentino et al., 2015; Pimentel et al., 1995). To quantify the long-term responses of soil to erosive factors, soil erodibility index (K), a rate of soil loss per rainfall erosion index unit, is determined based on measured inherent soil properties and soil profile characteristics (Römkens et al., 1997). In this analysis, the K factor is utilized to target the fields with higher soil erodibility potential, which can benefit more from potential soil conservation benefits via ILM. K values at a field level are extracted from SSURGO[4] data.

3. ILM site suitability approach

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[6] PRISM Climate Group, Oregon State University. http://prism.oregonstate.edu.

[7] National Hydrography Dataset. https://www.usgs.gov/core-science-systems/ngp/national-hydrography/national-hydrography-dataset?qt-science_support_page_related_con=0#qt-science_support_page_related_con

The proposed approach helps estimate land suitability for dedicated energy crops at the field level. Leveraging the results from BT16 scenarios and geospatial multicriteria method, we present an approach to score agricultural fields for suitability of energy crops production, such as *Panicum virgatum* (switchgrass). Specifically, it is meant to identify and score fields via site suitability index (SSI) (Wu et al., 2011) based on all the factors cited in section 2. Eq (3) below shows the equation used for SSI:

$$SSI = \sum(f_m w_m) \times \prod b_n \qquad \text{Eq (4)}$$

Where f_m is the fuzzy value of a criteria m, w_m is the weight of criteria m, b_n is the criteria score of constraint n (Binary value), and $\prod$ is the product.

This weight function is used to reflect the relative influence of the different parameters. In our case, we assume equal importance across factors. Binary values (0 and 1) are assigned to 3 constraint criteria that include land cover, crop rotation, and topography based on the site preference and acceptable range. Fuzzy-logic membership functions are built to determine the fuzzy value f_m of criteria considered, including AWS, NCCPI, FE, SOC, water leaching index, distance to water bodies, and soil erosivity index (K). Membership function is defined as below:

$$f_m = x_{sm} = \frac{x_{am} - x_{\min\_m}}{x_{\max\_m} - x_{\min\_m}} \quad \text{Eq (5)}$$

Where x_{sm} is the normalized value for criteria m in an assessed field, x_{am} is the average value in an assessed field for criteria m, x_{min_m} and x_{max_m} are the minimum and maximum values for criteria m in all assessed fields, respectively. Site suitability criteria and the scoring metric for each criterion is summarized in Table 1. Figure 1 displays a graphical representation of the SSI approach, in addition to data sources.

It is primordial to note that we focus on biomass potential over dryland (non-irrigated) areas, highly eroded, with low soil available water. The rationale is to ensure energy production without compromising food and crop production. As we prioritize fields with low NCCPI values, available water holding capacity and SOC for energy crops, the fuzzy value f_m is captured by the following equation:

$$f_m = 1 - x_{sm} \qquad \text{Eq (6)}$$

Table 1. Domains and criteria comprising the Multi-Criteria Site Suitability framework.

Criteria (Attributes)	Scoring metric
Land cover	b = 1: land cover is crop. b = 0: land cover is non-crop
Crop rotation	b = 1: non-specialty crop. b = 0: specialty crop
Available soil water storage within crop root zone depths	$f_m = 1 - x_{sm}$
National Commodity Crop Productivity Index (NCCPI)	$f_m = 1 - x_{sm}$
Field efficiency	Eq (1)
Topography (slope)	$f_m = x_{sm}$ b = 1: slope $\leq$ 16.70 degrees b = 0: slope > 16.70 degrees
Soil organic carbon in the 0-30cm layer	$f_m = 1 - x_{sm}$
Water leaching index	$f_m = x_{sm}$
Distance to water bodies	Eq (3)
Soil erosivity index	$f_m = x_{sm}$

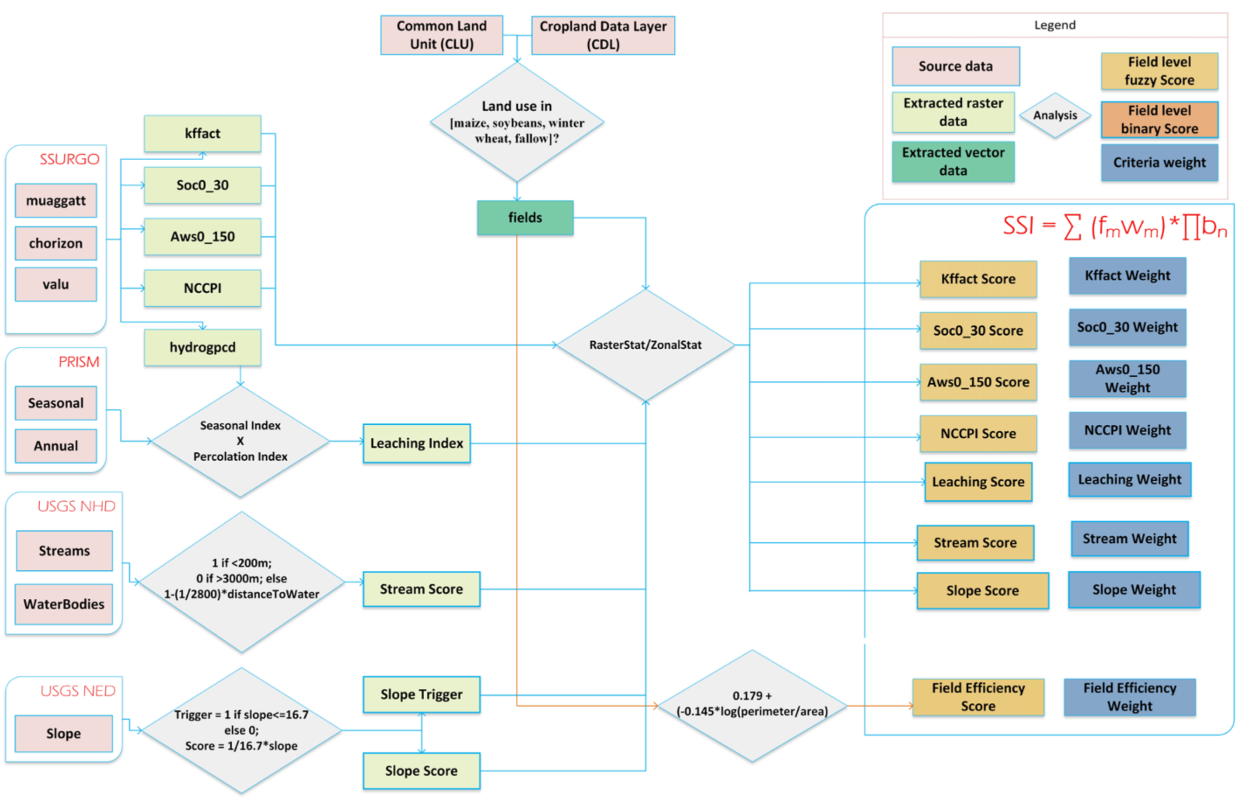

Figure 1: Graphical representation for SSI computation, and data source

4. ILM site suitability methodology

In this section, we present our methodology, that is, steps as well as the sequence we take to perform field allocation to energy crops by 2028. Using the scored fields, potential switchgrass feedstock supplies at a field level were modeled using POLYSYS outputs from Langholtz et al. (2016). POLYSYS is a partial equilibrium model that simulates the U.S. agricultural sector (De la Torre Ugarte and Ray, 2000), which has been used to explore potential future supplies and prices of biomass feedstocks (Hellwinckel et al., 2015; USDOE, 2011, 2016). One POLYSYS output is the county-level land-use transition matrix, i.e., the amount of land drawn from and allocated to each crop type in each year. This provides a basis to explore the county-level croplands that can transition from row crops to perennial energy crops subject to the weighted objectives in the present analysis.

Langholtz et al. (2016) study results, using POLYSYS, provide biomass supply potential estimates at a county levels along with detailed information on which crops could potentially be replaced for perennial energy crop production. As part of the outputs, POLYSYS also generates a proportion value, out of a given acreage per county (county partitioned), for each major crop type to transition to switchgrass production by 2028. Using this value, the switchgrass acres can be deduced using the following equation:

$$sgA_{c,i} = P_{c,i} * A_{c,i} \qquad \text{Eq (7)}$$

Where *sgA* is the switchgrass acres for county *i* drawn from crop acres *c, P* is the proportion estimate of county *i* that crop *c* will be transitioned to switchgrass production by 2028 and *A* the estimated crop acres for crop *c* in county *i* derived from 2019 CDL data.

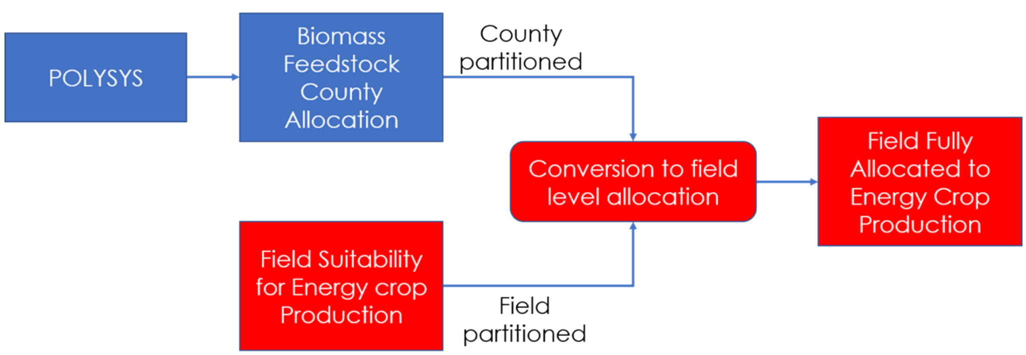

Figure 2: Component methods and data flow

Our contribution lies at 2 levels: *Field suitability for energy crop production* and *Field allocation to energy crop production,* seen in red in Figure 2. Using the site suitability approach (explained in section 3), we estimate field suitability for energy crop production, outputting field portioned map with suitability scores. The conversion to field allocation is done using both field and county partitions. As a result, we obtain the energy crop allocation at field level (Figure 2).

4.1. Field suitability for energy crop production

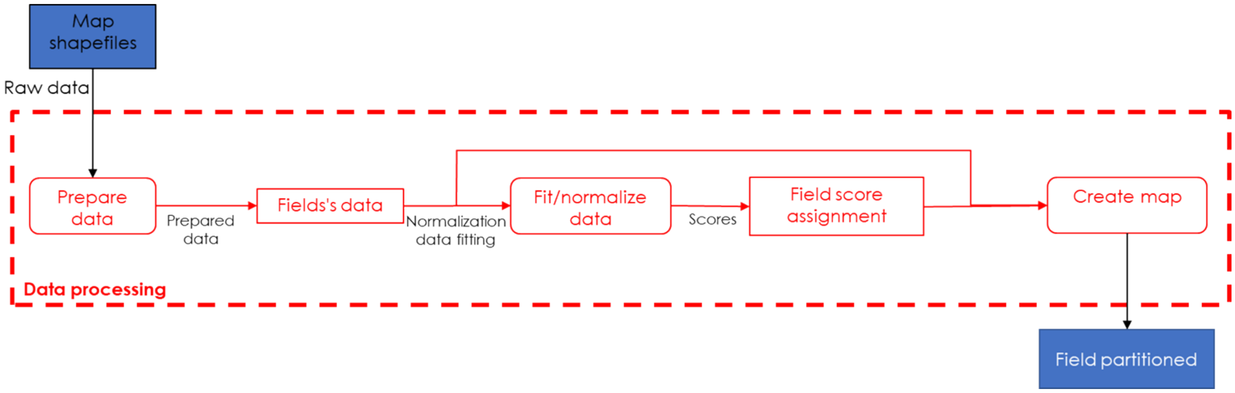

Figure 3: Data Flow Diagram of the field suitability.

Figure 3 describes the processing stages and data flow all through the field generation. The method contains three main processes, namely data preparation, data fitness modeling, and field/map creation. Data preparation process covers the data lifecycle from data acquisition to its processing and use. Field-level geodata information is stored into shapefiles, defining the field spatial extent in a grid format. These data are read and processed, using *Rasterio/RasterStat*, and *GeoPandas* Python libraries, which combines the capabilities of *Pandas* and *Shapely* to provide geospatial operations and handle multiple geometries. Field properties data (x_{sm} values in Table 1) are then normalized through the 2nd process, model fitness/normalization. By normalizing, we ensure that all input features/variables have the same scale, that is, bringing range of values between 0 and 1. This is done so that variables that are measured at different scales contribute equally to the model fitting & model learned function and do not create a bias. *Scikit-Learn* Python library is used for this step. In addition, machine learning algorithms perform better when features are on a relatively similar scale (Hale, 2019). Field score assignment helps redesign the parcels by SSI. Each field is assigned a score based on the values normalization performed earlier. Using bracket value system, with color code for instance, maps are designed, following SS values.

4.2. Conversion to field-level allocation

This step consists in converting county-level allocation to field-level allocation. We use POLYSYS results, providing the acreage percentage of each county, susceptible to transition. Using this acreage, we determine, based on field acreage and SSI, fields suitable for energy-crop production.

```
totalAcres ← totalAcres * prop
field.sort_values (by='ILM_SS', ascending=False, inplace=True)
appliedAcres = [ ]
FOR index, row IN field.iterrows( ):
    appliedAcres += row['CALCACRES']
    IF appliedAcres < totalAcres:
        field.loc[index, 'ecrop_score'] ← 1
    ELSE:
        BREAK
    ENDIF
ENDFOR
field_acre ← field [field ['ecrop_score'] == 1] ['CALCACRES'].sum( )
```

Figure 4. Pseudo code for Switchgrass Acreage allocation to fields.

Figure 4 displays an excerpt of the Python code used for acreage allocation. The value of variable *totalAcres* is obtained by Eq (7), representing the proportion of crop land likely to transition to switchgrass by 2028. The most suitable fields are selected for conversion to meet the land use transition goals. As fields are ranked based on their SSI value, *totalAcres* value is updated, subtracting the area of each field. In other words, the calculated switchgrass acreage is distributed to individual fields based on the associated crop type with the highest SSI score until the estimated acreage is completely allocated. Once all land is allocated, we sum up the acres of all fields considered.

5. Results

5.1. Study area

Our LSA is applied to 50 counties across 3 states (southern Nebraska, northern Kansas, and eastern Colorado) to assess and determine the suitability of each agricultural field for applying the ILM strategy for perennial switchgrass production. Figure 5 shows the boundaries of the region. This area is located in the midwestern part of the US, which is a nexus of agricultural productivity and bioenergy production (Moore et al., 2020). By tapping into its enormous renewable energy potential, this region is poised to become a leader in reaching renewable energy goals set by the US Department of Energy (DOE), and potentially a standard for other countries. Potential bioenergy resources —wood wastes, forest residues, agricultural residues, dedicated herbaceous and woody energy crops—, although widely distributed throughout the US are primarily concentrated in the midwestern states (Augustine et al., 2012; Hand et al., 2012). As the most important region that could lead the transition to smart bioenergy policies, it is important to carefully carry out LSA for energy crops in these states. The analysis is limited to lands starting in non-perennial row crops common to the region including corn grain, soybeans, spring and winter wheat, sorghum, oats, barley, cotton, and fallow.

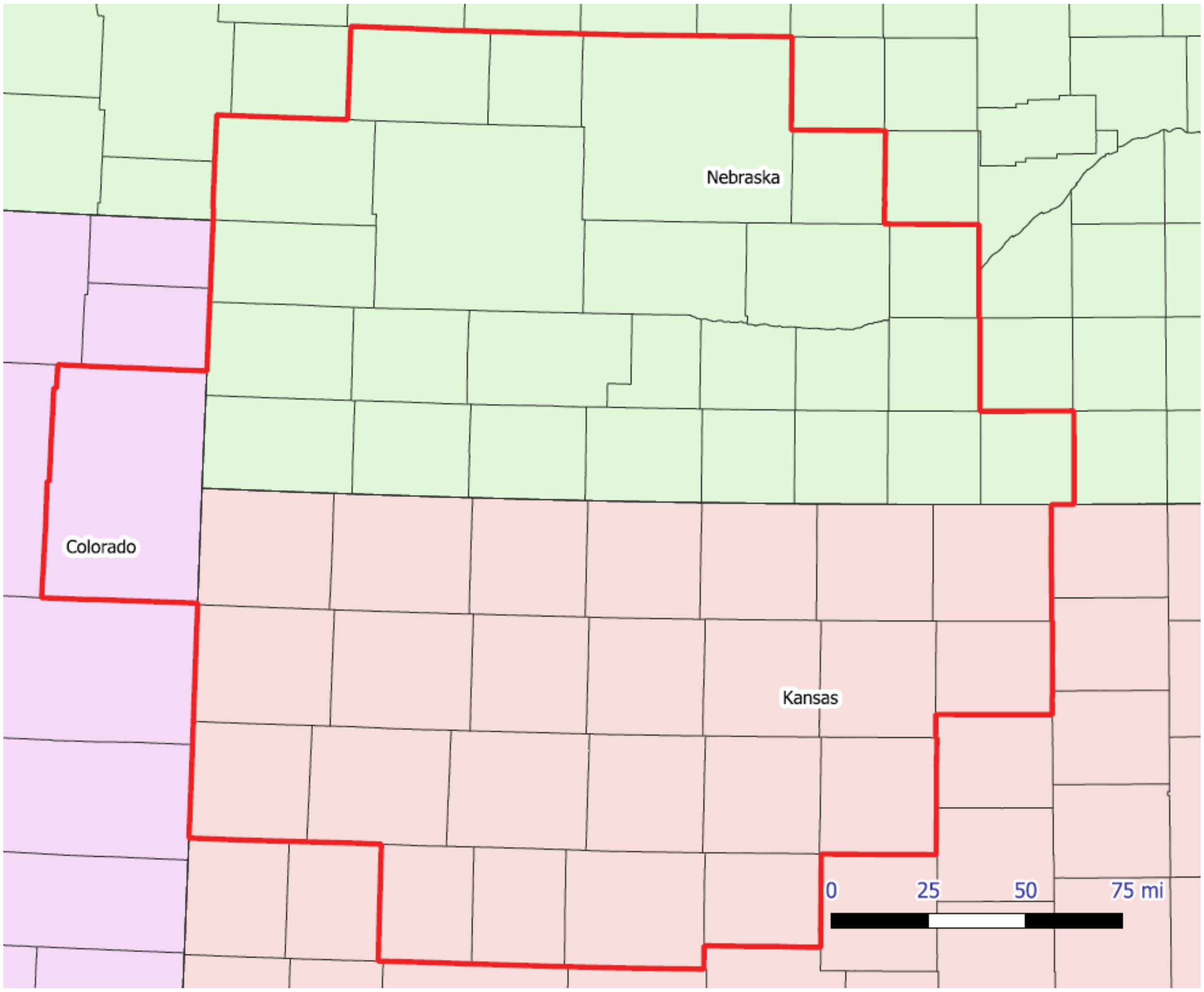

Figure 5: The region (outlined in red) spanning northeast Colorado, northwest Kansas, and southwest Nebraska used for ongoing ILM and Feedstock Technologies modelling. (Data Source: US Census Bureau[8])

Individual field boundaries are delineated using Common Land Unit (CLU) data from 2008. Developed and maintained by the USDA Farm Service Agency (FSA), CLUs represent the smallest unit of land with permanent, contiguous boundaries under a common land cover and land management schema. Although updated annually, current CLU data have not been publicly available since the enactment of The Food, Conservation, and Energy Act of 2008. The latest publicly available dataset is generated in 2008 (FSA, n.d.). However, it represents the best-known proxy for field boundaries available for wide-scale modelling efforts requiring individual field boundary delineation.

5.2. Field-level allocation

A total of 336,555 CLU parcels spanning the fifty-county region shown in Figure 6 are scored using the criteria listed in Table 1. Out of the initial field boundary group, 164,729 CLU parcels are identified with SSI scores above 0 – those scoring 0 are excluded because of crop rotation or slope restrictions via the binary scoring functions. The histogram (right) shows that most fields

[8] US Census Bureau (https://www.census.gov/geographies/mapping-files/time-series/geo/carto-boundary-file.html)

have an SSI around 0.4. Given the factors considered in section 2, we can see that most fields in area show relatively low suitability.

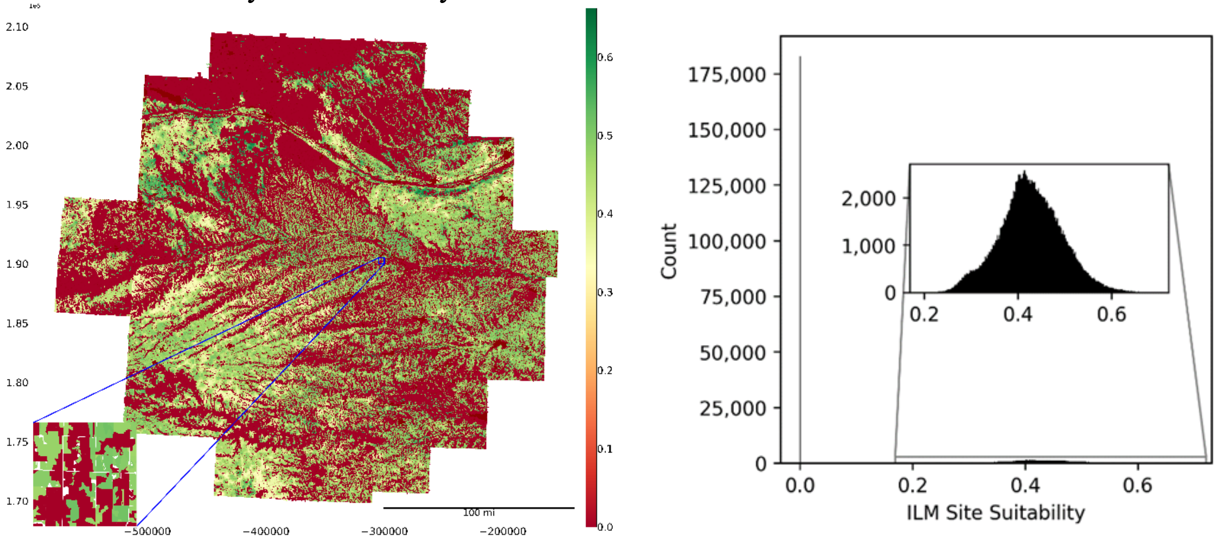

Figure 6. A map of the fields (left), using CLU[2] spatial field boundary data. Fields are scored for suitability for perennial energy crop production where low-scoring fields are symbolized in the red spectrum and high-scoring fields are symbolized in the green spectrum. The histogram (right) shows the SSI distribution for all fields in the region.

Figure 7 shows the resultant standardized distributions and ranges of the individual criteria used to calculate the final field SSI and present a profile of the fields investigated here. Stream proximity (distance to water bodies), soil organic carbon levels, soil erosivity (K Factor) and field efficiency show highest median values, indicating the fields in the study area are, for the most part, located close to water bodies and have high soil organic carbon and erosivity levels, as well as high field efficiency. These fields' soils also exhibit low NCCPI and AWS values, indicating low suitability for crop production and yield. Lack of available water would reduce root and hinder plant growth, which could ultimately limit productivity. These characteristics show the fields are non-profitable for agricultural crops, thus adequate candidate for energy crops production.

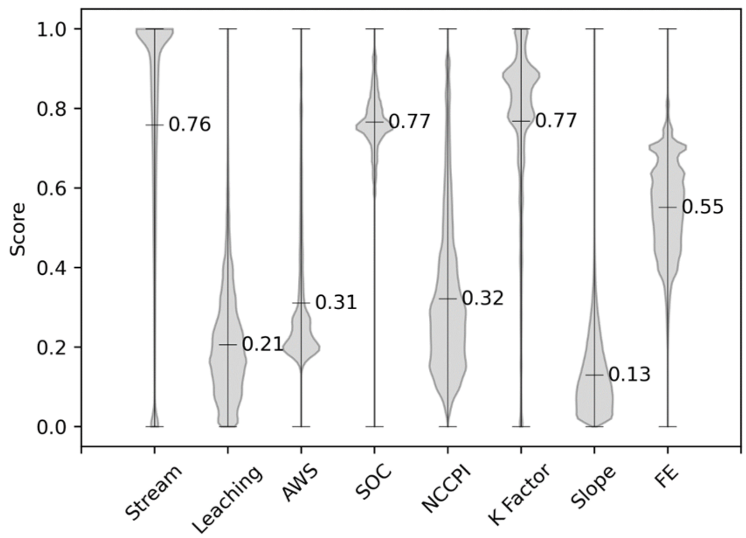

Figure 7. Data distributions of individual criteria with continuous scoring functions for the 50-county area.

A total of 9,431 fields are allocated to switchgrass production, using the field allocation method, spanning 17 counties. This geographical limitation originates from the fact that BT16 data only placed switchgrass production in 17 counties. This is what explains the darker spots at the top of the map, in Figure 8 (left). Figure 8 shows a map of the individual fields and the associated distribution of SSI values of switchgrass fields. It is important to note that the fields allocated belong to counties growing crops corn, barley, idle, soybeans, cotton, sorghum, oats, and wheat, as specified above.

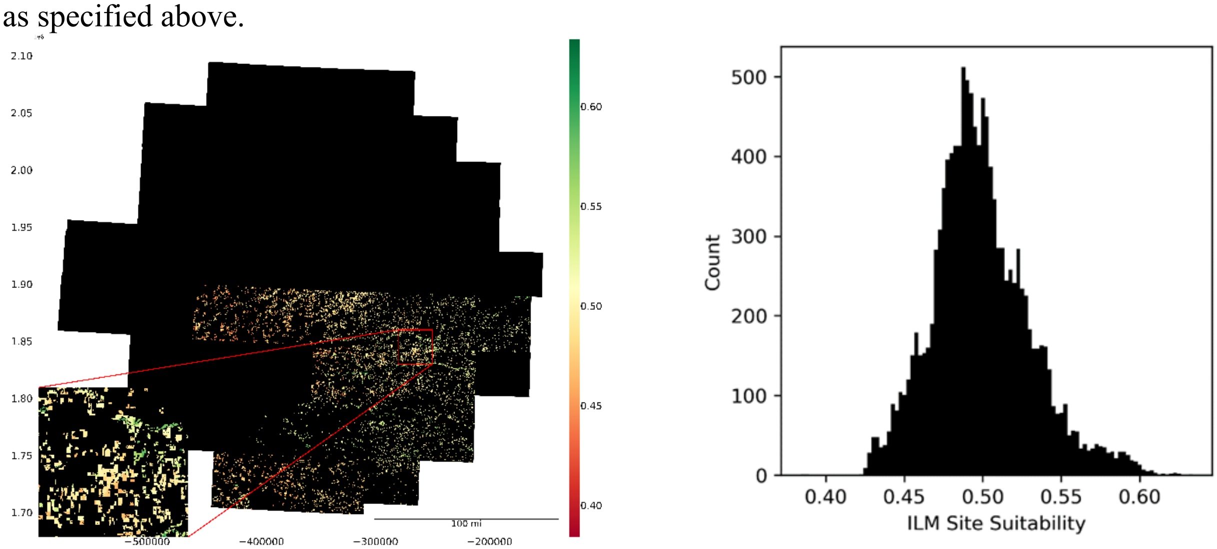

Figure 8. A map of the fields allocated to switchgrass production spanning 17 counties (left), using CLU[2] spatial field boundary data. The histogram on the right shows the SSI distribution for the switchgrass fields.

The histogram (on the right) displays the distribution of the SSI for allocated fields. We can observe that the switchgrass allocation favors higher scoring fields, which are in the state of Kansas (see figure 5). Most fields have their SSI around 0.5, indicating an overall good likelihood of success for bioenergy production in this region.

5.3. Method testing

To test the approach developed, we compare our results, both in acreage allocation and crop production, with the ones obtained by POLYSYS county-level estimates (Langholtz et al., 2016), by county GEOID. Similar to the *Comparison to Other Models* technique (Sargent, 1999, 2004), by comparing our results to the ones of models that have been validated, we aim to build credibility in our model, and establish an argument that the model produces sound insights.

```
field_prod ← field [field ['ecrop_score'] == 1] .copy( )
FOR index, row IN df_field_prod.iterrows( ):
  field_prod.loc[index, 'energy_crop_production'] = yieldField * row['CALCACRES']
ENDFOR
field_production ← field_prod [field_prod ['energy_crop_production'] ].sum( )
```

Figure 9. Pseudo code Switchgrass Acreage production

In Figure 9, we show the excerpt of the Python code used for switchgrass production, based on the field allocation previously done. The variable *yieldField* corresponds to the potential for yield of the field, and is deduced from the yield at the county level, gathered from Langholtz et al. (2016). The value of *yieldField* is obtained using the following equation:

$$yieldField = yieldCounty \frac{NCCPI_{field}}{NCCPI_{county}} \qquad \text{Eq (8)}$$

Where *yieldCounty* is the yield value at the county level, $NCCPI_{field}$ and $NCCPI_{county}$ are indexes at the field and county levels, respectively. Once the switchgrass production is computed for each field, we aggregate them by county. Figure 4 shows the excerpt of the Python code used for switchgrass acreage.

By using county-level data to obtain field-level data, we are able to infer high-resolution information from low-resolution variables, thus capturing more details, in our case, soil fields variability. This is a critical aspect affecting yield and ultimately production, not accounted for at the county level. The results of the comparison analysis (Figure 10) indicate that our method fares better in certain areas as opposed to others. When we aggregate the values, the difference in results is less significant, however. Total switchgrass acreage allocation using our approach was 806,582 acres and the POLYSYS estimate is 791,443 acres. Total switchgrass production (in dry tons) with our approach is 3,174,146 dt and the POLYSYS estimate is 3,135,704 dt. Overall, there is about 2% and 1.2% of difference in acreage allocation and crop production, respectively.

Discrepancies may be due to the difference in crop-specific acreage estimates by county. In our method, we calculate crop type acreages by spatially intersecting CLU field boundaries and CDL data and assigning crop types to fields based on the majority of CDL pixels categorizing the crop type. POLYSYS crop acreage estimates are primarily derived from USDA National Agricultural Statistics Service (NASS) data and augmented with CDL data when specific county NASS metrics are not available. Another reason may be heterogeneity in fields. As shown in Eq (8), yield varies by field since each field has a unique NCCPI. Summing these yield values would amount to a different value than the one obtained from POLYSYS. Although this difference in output is welcome and expected, as it justifies the needs for more granularity in bioenergy potential estimation in the future, the difference between these results output is key. In fact, it is indicative of our model correctness. Providing output "close" to an already validated model output builds confidence in our model performance and removes barriers and objections to its uses for bioenergy suitability studies.

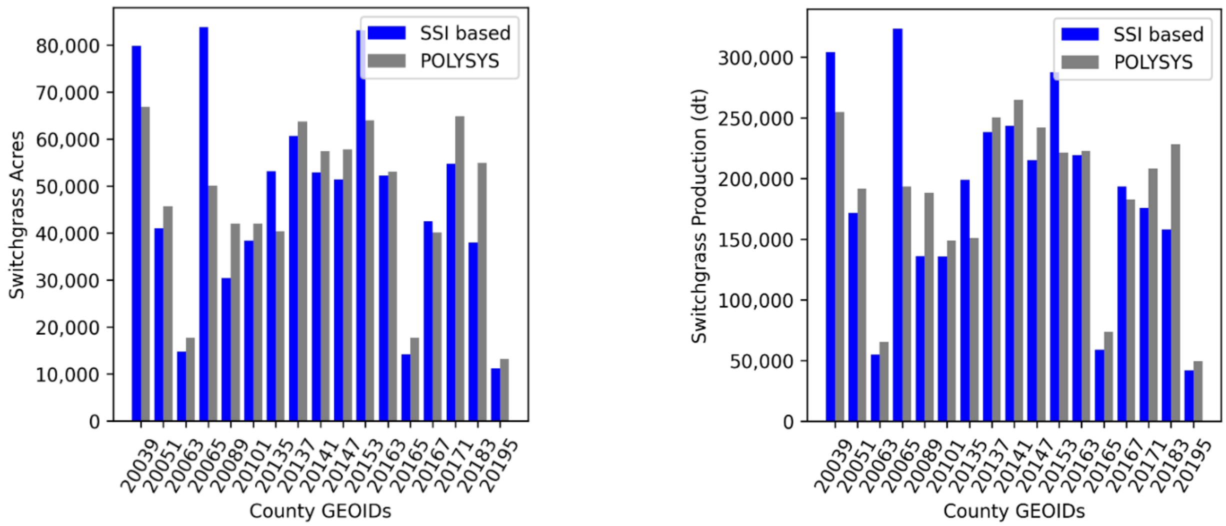

Figure 10. Comparison analysis results of county aggregate field-level switchgrass acreage and production estimates of the probability-based method and POLYSYS county-level estimates.

6. Conclusion

The outlook for biomass resource production in the US holds promise. When looking for a sustainable bioenergy future, a crucial need is accurate assessments of biomass availability. County-level estimates provide useful information but do not fully reflect fields constraints and variability across fields. This work bridges this gap by capturing these geospatial differences, which offer opportunities for more precise crop management decisions and a thriving bioeconomy.

Using geospatial analysis, machine learning, and optimization techniques, we develop a GIS/spatial multicriteria approach using a linear fuzzy-logic model to calculate the SSI for agricultural fields. This index, considering several factors that include land cover, crop rotation, water storage, commodity crop productivity index, field efficiency, topography, soil organic carbon, leaching index, distance to water bodies and soil erosivity, helps assess field suitability for switchgrass, minimize potential negative environmental impacts, and maximize environmental services. Using a scenario of potential future switchgrass acreage and production at the county level, we estimate switchgrass acreage and production with higher resolution, at the field level, for a more precise estimation of bioenergy potential in the US Midwest. Estimates at the field level can be decisive for the sustainability of biofuel industries and U.S. Department of Energy Bioenergy Technologies Office objectives, especially considering heterogeneity in fields properties across counties.

This work makes progress toward more accurate land suitability assessment and enhancement of economic and environmental benefits from biomass production. Comparison with county-level estimates show good performance overall, with about 2% and 1.2% difference in acreage allocation and crop production, respectively. The methodology defined in this study can be useful for bio-energy industries, and associated stakeholders to evaluate potential pocket areas for energy crop production. Additionally, the outputs can be used as a communicative tool with potential producers. This level of analysis can provide insight and geospatial details on site suitability.

There are however some limitations to the study. One, the data used for field boundaries, using Common Land Unit, date from the year 2008. Given the enactment of The Food, Conservation, and Energy Act of 2008, Title I - Commodity Programs, Subtitle F - Administration, Section 1619 on May 22, 2008, the Farm Service Agency has been barred from publicly sharing Common Land Unit records (FSA, n.d.). Using information from that far back in time may not reflect recent changes in fields' characteristics and limits, potentially raising concerns as to the practicality of results obtained for bioenergy potential in the future. Two, the factor weighting is subjective. We assume equal importance for factors for simplification. However, stakeholders may see certain indicators more important than others. This inevitably affects the ranking selection method, which is based on the highest score for fields (section 4.2). A different weighting approach could potentially provide different field rankings, and ultimately different acreage and production. Because the approach emphasized highest scoring, it is important to determine weights accordingly, as to obtain useful field suitability distribution.

For further suitability studies, selection of climate could be proposed as a factor of interest. With the long-term shifts in temperatures and weather patterns that could have potential impact on soil properties and processes (Brevik, 2013; Karmakar et al., 2016), it is important to develop framework and quantitative approaches to estimate these impacts, and the ultimate implications on bioenergy future in the US. This will provide opportunities for improvement in land suitability analysis.

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