

Optimizing site selection for solar PV panel using AHP in marginal Kansas.

by

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Abstract

Energy demand in the United States is expected to increase by 15% between 2020 and 2050. With increasing demand our reliance on non-renewable energy is rapidly decreasing. While the adoption of renewable energy has significantly decreased CO₂ emissions, a major limitation still lies in the deployment of these energy structures. Solar energy has become one of the most reliable non-renewable energy resources for its green and clean attributes. However, the installation of solar photovoltaic panels has the potential to compete with agricultural land cover due to their vast land requirement, approximately 4-5 acres of land for 1MW capacity. The state of Kansas is one of the top 10 sunniest states of the United States, however, this sunflower state is lagging behind in terms of solar-based energy generation. My thesis focuses on identifying suitable sites for solar photovoltaic plants in marginal lands that are unproductive, underutilized, and unfavorable for agricultural production. Firstly, the thesis adopts an overlay approach to identify marginal lands in Kansas. Along with quantifying and identifying marginal lands, the thesis also attempts to validate the quantified marginal lands in Kansas. According to my result, the state of Kansas covers approximately 0.4736 million hectares or 1,170,185.54 acres of marginal lands. Secondly, by utilizing secondary data and experts' opinions through a Qualtrics survey, my research aims at identifying suitable SPV sites in Kansas. This thesis adopted a GIS-based multi-criteria approach to rank the marginal land cover in Kansas from most to least suitable for SPV deployment. The overall SPV suitability map shows that only 770 km²/ 0.077 million hectares of suitable marginal lands carries the highest potential for developing SPV power plants in Kansas. However, approximately 90% of the suitable marginal lands are very high to moderately suitable for SPV deployment, which indicates a high potential for future SPV projects in Kansas. Finally, by identifying the most suitable sites in marginal lands, my research

broadly aims at promoting SPVs in Kansas while avoiding land covers that are utilized for food production.

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Chapter 1: Introduction

1.1 Motivation

Growing energy consumption (both renewable and non-renewable) has significantly spurred the economies of numerous countries around the world. This consumption has threatened the global climate with an unprecedented increase in carbon dioxide (CO₂), and methane concentrations resulting in direct or indirect environmental disturbances such as, biodiversity loss, deforestation, and water, and soil pollution (Jin and Kim, 2018; Janke, 2010; Pata, 2018). Greenhouse gas (GHG), a direct byproduct of fossil fuel combustion has become a major concern for international organizations (such as the Intergovernmental Panel on Climate Change (IPCC), the United Nations Framework Convention on Climate Change (UNFCCC)) and the government (Jin and Kim, 2018). These organizations indicate energy production and consumption as one of the major drivers of GHG emissions.

To overcome the detrimental effects of GHG, solar energy, wind power, hydropower, geothermal energy, biomass, and tidal energy are presented as potential sources of renewable energy to reduce GHG emissions (Shahzad, 2012). Aside from being infinite in nature, these renewable resources are more favorable considering their reduced environmental impact when compared to fossil fuels. As a result, global electricity generation from renewable resources has increased almost tenfold between 1965 and 2022 (from 941.18 TWh (Terawatt hour) to 8,538.50 TWh) (Ritchie et al., 2024). Over the past several decades, many regions have experienced a remarkable surge in their renewable energy consumption. Starting from a modest 427.05 TWh in 1970, total renewable energy output in North America has increased to 1517.79 TWh in 2022

(Energy Institute). Among different sources of renewable energy, wind and solar energy lead the energy sector (US Energy Information Administration,2023).

The United States has seen a remarkable shift from non-renewable to renewable energy sources (US EIA,2023). One of the most significant contributors to this growth has been solar photovoltaic (SPV) power plants and related technologies that have emerged as a tangible renewable energy option (Markvart and Castaner, 2003; Goetzberger and Hoffmann, 2005), and have gained recognition for generating clean, noiseless, and eco-friendly electricity directly from sunlight. The US solar industry has witnessed a significant expansion from 59.349 trillion Btu in 2000 to 877.54 trillion Btu in 2023. U.S. Energy Information Administration's (EIA) Quarterly Report states that in 2023, the US solar market added 6.5 GWdc (Gigawatt Direct current) of capacity (a 36% increase from Q3 2022). This capacity accounts for 48% of all new power-generating capacity added to the US grid during the first three quarters of 2023, a substantial increase from the 4% share it held in 2010 (Feldman, et al., 2023; Solar Energy Industries Association, 2023).

Among the states in the US, California, Florida, Texas, Colorado, and Nevada contribute the most to the US solar market. According to the NREL Fall 2023 Quarterly Report, about 39% of solar PV capacity installed in the US in 2023 is in California, Florida, and Texas (Feldman et al., 2023). California leads the nation with an installed solar capacity of 46,874 MW, powering over 13.9 million homes, solidifying its pioneering position in solar market. This vast solar capacity is supported by \$102.8 billion in solar investment and contributes 28.16% of California's energy. Texas and Florida also demonstrate strong solar adoption (Table 01), with significant installed capacity and considerable number of houses powered by solar, underscoring the growing importance of solar energy in these states.

Despite strong potential for solar energy generation, Kansas does not exhibit the same level of performance as other states (Solar Energy Industry Association). Kansas ranks 45th in the US in terms of installed solar capacity in 2024 (Solar Energy Industries Association, 2024). Despite being one of the top 10 sunniest states in the US, solar energy contributes only 0.35% to Kansas's state energy profile, which is lower than other states with identical sunshine conditions. According to SEIA (2024), the current installed solar power generates 152 MW of electricity, powering a mere 21,952 homes in Kansas. Investment in solar energy is the lowest in Kansas among the leading states in the US, with approximately \$300 million (Table 1.1).

Table 1.1: A comparative analysis of solar energy development in Kansas versus the top ten solar energy-producing states in the USA

Factors	Installed solar capacity	National Ranking	Homes powered by solar	Solar rebates and tax incentives	Contribution to solar to state energy profiles (%)	Solar investment (Billion \$)
Kansas	152	45	21,952	12	0.35	0.304
California	46,874	1	13,904,267	153	28.16	102.8
Texas	22,872	2	2,677,486	115	5.82	27.8
Florida	13,912	3	1,663,089	72	6.75	20
North Carolina	9,310	4	1,169,056	68	9.34	12.
Arizona	7,675	5	1,173,331	51	10.15	18.8
Nevada	6,382	6	1,150,989	28	25.93	11.1
Georgia	5,913	7	710,506	35	6.08	6.5
New York	5,560	8	980,034	95	5.01	11.7
New Jersey	5,276	9	904,948	50	7.44	14.8
Massachusetts	5,070	10	912,036	80	24.38	11.2

Data Sources: Solar Energy Industry Association and North Carolina Energy Technology Center.

Although Kansas ranks among the lowest among the 50 states in the US solar market, it has experienced considerable growth in both utility-scale and small-scale solar photovoltaic installations between 2015 and 2022 (EIA.GOV). The net electricity generated from small-scale SPV, which includes residential and commercial solar systems, has increased from 4.6 GWh in 2015 to 86.9 GWh in 2022, reflecting a strong trend in the adoption and production capacity of small solar installations (EIA.GOV). Meanwhile, electricity generated by utility-scale SPV,

which are larger solar farms and power plants (more than 5MW capacity), has increased from 1.806 GWh in 2015 to 74.391 GWh in 2022, representing an increase of approximately 72.585 GWh (U.S. Energy Information Association). The total electricity generation from all types of SPV has increased from 6.4 GWh in 2015 to 161.3 GWh in 2022, showcasing solar energy's rapidly increasing role in Kansas's energy sector. However, while approximately 50% of the total electricity generation in Kansas was derived from renewable resources in 2022, approximately 99% of this electricity originated from wind power (U.S. EIA, Electric Power Monthly, 2022).

While there is potential market for more SPVs in Kansas, installation of solar photovoltaic demands a large swath of land, which could compete with areas designated for agriculture, potentially exacerbating the existing competition for available land resources between agri-based food production and energy generation in the rural US (Calvert and Mabee, 2015; Khanna et al., 2021; Valentine et al., 2012). For instance, utility-scale photovoltaic (PV) facilities have gained popularity for their technical feasibility, economic competitiveness, and potential for grid integration (Mendelsohn et al., 2012). Despite the popularity, a key challenge is land requirements, with approximately 2.5 to 3.5 hectares per MWac (Megawatt alternating current) of installed capacity (Ong et. al., 2011). In the USA, the deployment of utility-scale solar facilities on farmlands fuels the debate about the loss of valuable farmlands, as solar development can bring more income than cultivating any crops (Kirk Hall et al., 2022; Grout and Ifft, 2018). For instance, nearly 30% of utility-scale solar projects in the U.S. were situated on croplands and pastures (Hernandez et al., 2015). Moreover, in California's Central Valley, a highly productive agricultural region, over 27,000 acres has been occupied by solar projects in 2015 (Kirk Hall et al., 2022). Therefore, presenting an alternative way to produce energy without posing a threat to prime farmland can effectively address the dual objectives of meeting

increasing global energy demands and ensuring food security. However, aside from considering alternative land cover, another aspect to consider for solar PV deployment is land ownership (Hernandez et al., 2014). In other words, solar installation on private land tends to have a higher land use efficiency (higher economic return) compared to those on public land, indicating that land ownership can also influence the efficiency of land use in solar energy production (Hernandez et al., 2014).

1.2 Problem Statement

Kansas ranks among the top three states in wind-powered electricity generation. While wind energy is one of the non-depleting, non-polluting energy sources with minimal land requirements, it also has its own sets of limitations, such as high total system cost, noise pollution (Wang and Wang, 2015), bird and bat fatalities (Wang and Wang, 2015), and regular maintenance requirements (Lu et al., 2002). Owing to these limitations, investing more in solar energy could be a more feasible alternative to meet growing energy demand and ensure energy security in Kansas.

Kansas has great potential for Rural SPV power generation and has been ranked as the 3rd in the contiguous United States (Lopez et al., 2012). Despite having high potential, there are only fifty solar companies operating in Kansas, including manufacturers, installers, and developers, contributing to Kansas's solar energy market. The adoption of solar energy is increasing at a steady pace in Kansas compared to neighboring states (Solar Energy Industry Association, 2023). Moreover, a significant portion of electricity generated by solar power comes from utility-scale solar and roof-top solar panels (EIA.GOV). Utility-scale SPV technologies have faced community opposition due to vast land requirements and associated long-term impacts on biodiversity and land use (Gross, 2020). Furthermore, utility-scale and commercial scale also

have an impact on aesthetic views. Microgrid SPV ($\leq 1\text{MW}$ generative capacity) technologies are deemed as a green alternative which can operate and produce, distribute, and store electricity with or without the support of a centralized macro-grid (Chan et al., 2017). While adoption of microgrids is receiving worldwide recognition for expanding electricity in remote areas of developing countries (Schnitzer, 2014; Bhattacharyya, and Palit, 2014), Kansas has only 3% of total microgrid projects operated in the US (Ajaz, 2009).

While there is a need for solar microgrid and other solar projects in Kansas to potentially enhance energy resilience, such initiatives have the potential to threaten agricultural land since solar microgrid installation requires long-terms leasing of land, which creates a clash between food production and energy consumption. To fill this gap between increasing energy demand and land for food production, this thesis will focus on utilization of marginal agricultural and other lands. These lands are physically, socially, and environmentally unproductive landcover that results in a diminished economic yield. Among potential marginal lands are the Conservation Reserve Program (CRP) lands, a voluntary long-term program where landowners and producers receive incentives to set aside lands considered as marginal and environmentally sensitive land from agricultural production. Kansas has approximately 1.976 million acres of conservation reserve program lands (USDA Farm Service Agency, 2023). These marginal lands are mostly eroded lands with poor drainage quality, which are not suitable for crop production.

There has been a significant volume of research (Khanna, et al., 2021; Kang et al., 2013; Milbrandt et al., 2014) that has focused on defining and identifying marginal lands. However, a restricted number of studies (Jiang, et al., 2021; Milbrandt et al., 2014; Emery et al., 2017) has attempted to identify, quantify, and validate marginal lands using geospatial analysis. Moreover, there have been no studies that focused on utilizing marginal lands as suitable locations for SPV

within the state of Kansas. Thus, the general objective of this study is to identify optimal locations for the deployment of solar photovoltaics (SPV) that do not conflict with productive agricultural lands in Kansas. More specifically, this thesis has the following objectives: (1) to identify marginal lands that are suitable for SPV in Kansas, (2) to evaluate the potential use of CRP lands as suitable sites for SPV development, and (3) to conduct a sensitivity analysis based on selected siting criteria. In developing these objectives, I seek to answer the following research questions;

Research Question 01: Can CRP lands be used to validate marginal land for SVP location suitability?

Research Question 02: What is the potential of utilizing marginal lands for solar photovoltaic deployment in Kansas and how does sensitivity analysis impact the robustness and reliability of site selection outcomes in MCDA (Multicriteria decision analysis) for solar microgrid development?

To accomplish the research objectives this thesis is organized into four chapters.

This chapter provides a brief overview of the problem under study.

The *second chapter* introduces a framework to identify marginal lands within the State of Kansas that could be utilized for micro-grid solar photovoltaic (SPV) development. Our framework encompasses both soil biophysical characteristics and specific land cover that have been intensively discussed in the literature. This chapter extensively discusses the major criteria and the associated thresholds needed to evaluate and separate marginal lands from other land use/ land covers. By distinguishing marginal land, we can further identify the potential marginal land parcels that can be utilized for solar photovoltaic deployment.

Chapter 3 will provide a thorough understanding of the methods to identify the most suitable locations for micro-grid solar photovoltaic (SPV) deployment on the marginal lands (discussed in chapter 02). This chapter identifies sets of criteria that have the most influence on SPV deployment. A multicriteria decision method (Analytical Hierarchy Process or AHP) is adopted to help determine suitable location for SPV development. Lastly, this chapter produces maps to show the most to least feasible location for SPV sites in Kansas on marginal lands.

Chapter 4 will present a discussion on final findings on marginal land and suitable sites for SPV development within the state of Kansas, recognizing the limitations of this research. This chapter will also suggest potential future work.

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Chapter 2: Marginal Land Identification

2.1 Summary

This chapter introduces a framework to identify marginal lands within the State of Kansas that could be utilized for micro-grid solar photovoltaic (SPV) development. My framework combines both soil biophysical factors and specific land cover characteristics that have been intensively discussed in the literature. The chapter extensively discusses the major criteria and the associated thresholds to evaluate and separate marginal lands from other land use/ land cover categories. While delineating marginal land cover for Kansas, my research broadens its focus by assessing the identification of marginal lands generated. To validate the identification of marginal land cover, I utilized Conservation Reserve Program land cover that serves as field observation in the validation process. This analysis will be conducted at the level of the Common Land Unit (CLU) boundaries, with the CLU boundary data obtained from the USDA FSA (USDA Farm Service Agency). Lastly, by delineating marginal lands, I will further identify potential marginal land parcel that can be utilized for solar photovoltaic deployment.

2.2 The concept of Marginal Land: Definition and Quantification

Researchers have defined marginal lands in numerous ways. The concept of ‘marginal land’ was first introduced in the early 19th century through the Theory of Rent by David Ricardo (Ricardo, 1817). The scientific investigation of defining marginal land was inaugurated by Peterson and Galbraith (1932). Since then, marginal land has been defined and identified in terms of their physical attributes, productivity, and economic output. Increasing population, climate change, and associated pressures on land cover, the concept of marginal land has evolved

in recent decades (Kang et al., 2013). Moreover, these definitions also vary across countries, regions and organizations based on their objectives behind defining marginal lands (Baldock et al., 1996; Tang et al., 2010; Wells et al., 2018). Thus, the attributes that deem a piece of land ‘marginal’ in one scenario or objective may be deemed ‘productive’ in a different scenario or other objectives (James, 2010; Dale et al., 2010).

A conventional definition of marginal land is characterized by low productivity and minimal/reduced economic return (Peterson and Galbraith, 1932). In most cases, these lands are infertile and hazardous/environmentally risky parcels of lands that can no longer be utilized for agricultural cultivation (Robertson et al., 2008; Wiegmann et al., 2008; Barbier, 1989; Wu et al., 2010). According to USDA-NRCS, marginal land refers to those tracts of land that are characterized by certain constraints such as soil erosion, wetland presence, soil salinization, and inadequate suitability for crop cultivation or production (Kang et al., 2013). In addition to defining marginal land as unproductive (Yang et al., 2020; Kang et al., 2013; Cai et al., 2011; Milbrandt et al., 2014), scholars have simultaneously employed various terms to denote marginal land, such as, abandoned land (Milbrandt et al., 2014; Field et al., 2008), barren lands (Milbrandt et al., 2014), moderate ecosystem productivity (Cai et al., 2011), and degraded land (Niblick and Landis, 2016). Figure 2.1 provides an overview of terms researchers have utilized to define marginal lands.

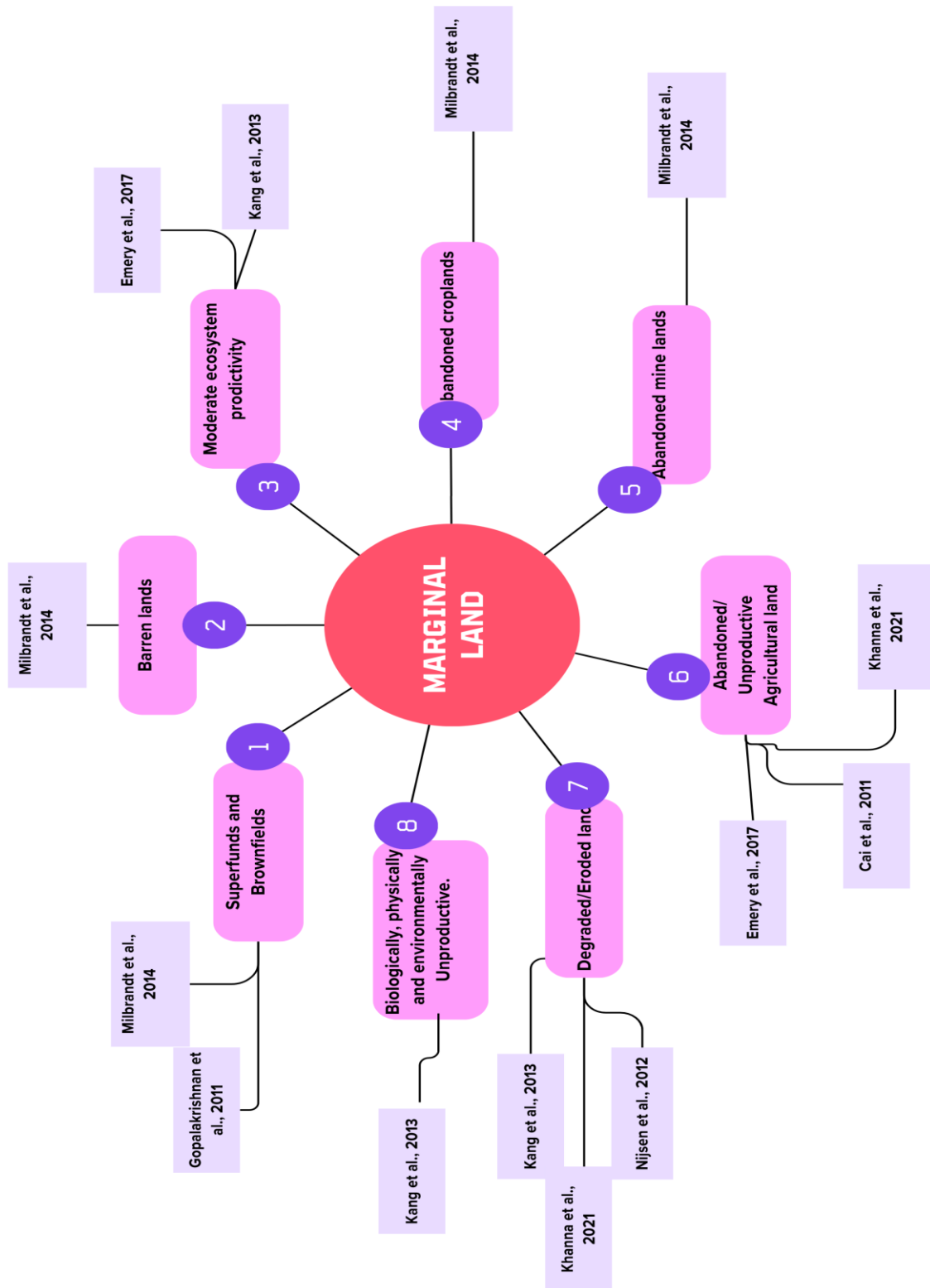


Figure 2.1: Definitions adopted by scholars for marginal lands.

Marginal lands have gained significant attention worldwide owing to their utilization for bioenergy crop production (Richards et al., 2014; Milbrandt and Overend, 2009, Vuichard et al., 2009). Their limited productivity and economic value are suitable for cultivating bioenergy crops (Nijssen et al., 2012; Wu et al., 2010). Due to the eclectic nature of marginal land, researchers have adopted different methods to quantify marginal land based on their specific management goals (Jiang et al., 2021; Khanna et al., 2021; Milbrandt et al., 2014; Kang et al., 2013; Cai et al., 2011). Table 2.1 describes the various ways researchers have described the factors and criteria used to characterize marginal lands.

Table 2.1: Research focused on defining and identifying marginal lands based on reviewed literature.

References	Factors/Criteria Based on Biophysical Parameters				Factors/Criteria By defined Land cover
	Climatic Temperature and Humidity	Physical • Soil erosion, • Land productivity, • Slope, • Rock fragment • Bedrock depth, • Flooding, and ponding.	Socio-ecological Potential threats to biodiversity, wetlands, and pollution; and Buffer zones or corridors	Economic (Break-even price)	
Khanna et al., 2021		✓		✓	(Degraded land, Abandoned agricultural land, Idle land, Buffer zones, Moderate ecosystem productivity, Abandoned mine lands, EPA sites include Brownfield, federal/non-federal Superfund, Landfills, Barren lands, Land cover data based (LCC)).
Wu et al., 2010		✓			
Emery et al., 2017		✓			✓
Meehan et al., 2017	✓				
Kang et al., 2013	✓	✓	✓	✓	
Cai et al., 2011	✓	✓			
Sallustio et al., 2018				✓	
Gopalakrishnan et al., 2011		✓	✓		
Well et al., 2003		✓			✓
Milbrandt et al., 2014					✓

For instance, Kang et al. (2013) developed a hierarchical framework to quantify marginal lands, with the specific objective of identifying suitable locations for bioenergy crop cultivation. These authors identified marginal lands under four categories, considering physical aspects (steep slope, flood prone areas, and eroded soil) aspects, biological factors (low pH, drought, salinity) factors, environmental-ecological characteristics (EPAs and hazardous zones), and economic criteria (low economic return) marginal lands (Figure 2.2).

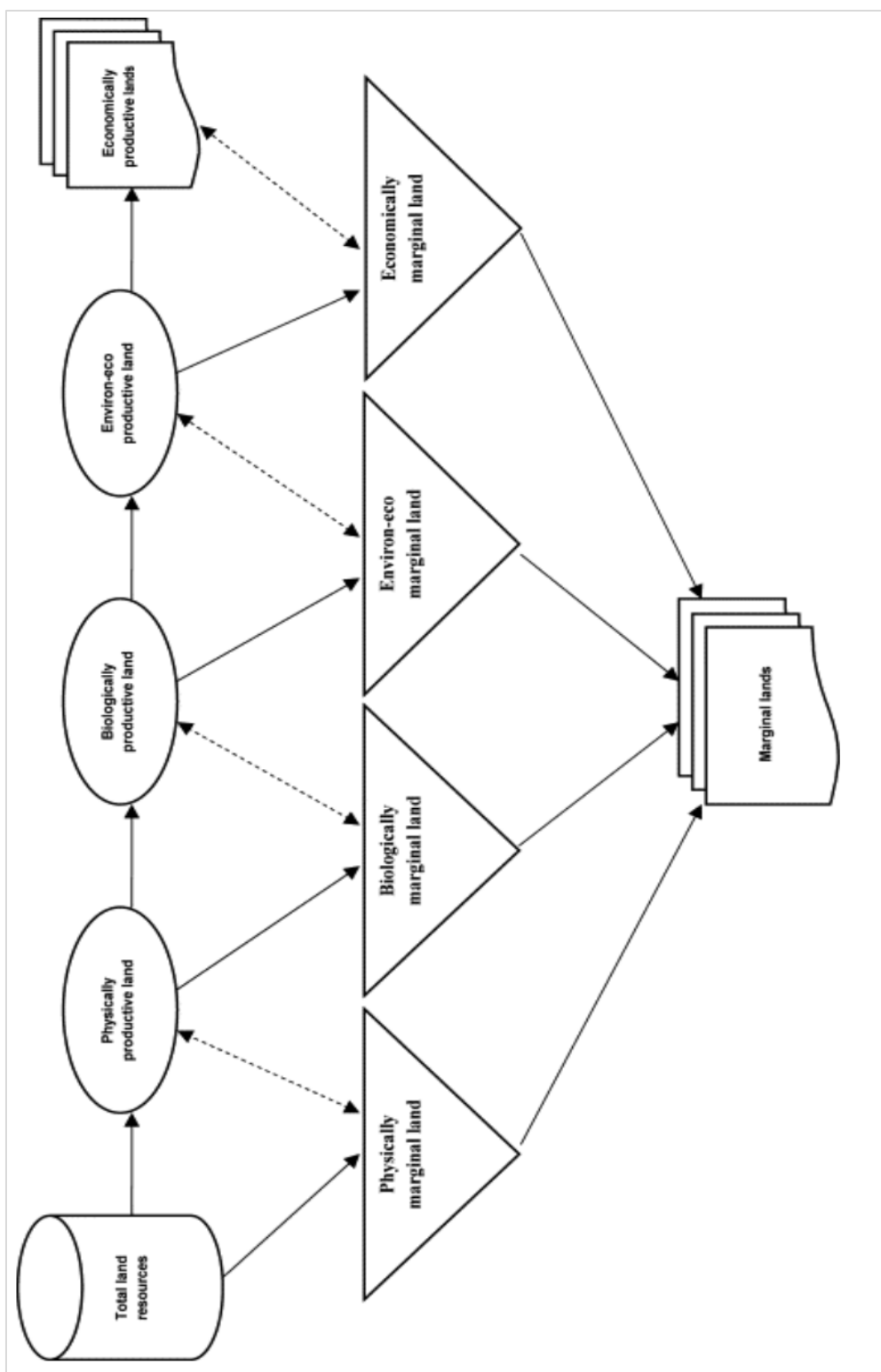


Figure 2.2: A hierarchical framework to define marginal land (Developed by Kanq et

Other researchers such as Khanna et al. (2021) defined marginal land use into several categories based on biophysical suitability, historical and current land use, and economic marginality. In this study biophysical suitability is identified by three approaches: applying suitability thresholds to biophysical grids (e.g., slope, soil pH, soil salinization, drainage, etc.); mapping derived productivity indices (an overall composite land productivity index); and identifying areas of degraded land quality (soil fertility loss and degradation). Also, historical marginality was assessed by identifying lands that have been abandoned from agriculture or cropland (including lands under CRP). Finally, economic marginality can be quantified by the economic returns from a parcel of land. The rationale behind their proposed framework is to identify potential marginal land that was used to cultivate bioenergy crops, while reducing pressure on food croplands.

With an aim to measure the potential of renewable energy on marginal lands Milbrandt et al., (2014) defined marginal lands as the lands that are marginalized due to natural and anthropogenic forces. Milbrandt et al. (2014) recognized that undesirable lands with less competition and that are undesirable could be a feasible option for installing renewable energy projects that could improve community relationships and provide jobs and opportunities. The authors identified and quantified marginal land by considering the following criteria, (a) abandoned lands, (b) abandoned croplands, (c) abandoned mine lands, (d) EPA sites, (e) landfills (f) Right-of-Ways (ROW), and (g) barren lands.

While there is widespread research conducted on defining marginal lands, limited research has focused on quantifying marginal lands. In general, quantitative logic and fuzzy logic modelling can provide non-spatial quantification of marginal lands. Nevertheless, the adoption of

GIScience and remote sensing in land use science has revolutionized the concept of quantifying land use. Based on the abovementioned reviewed literature, we have identified five methods that researchers have widely adopted in quantifying marginal lands (Figure 2.3/Table 2.2). They are (a) quantitative logic sets, (b) overlay GIS analysis/overlay analysis, (c) fuzzy logic modelling, and (d) remotely sensed time series land cover analysis. Gopalakrishnan et al., (2011) conducted an overlay analysis in ArcGIS to identify marginal lands based on certain criteria (e.g., soil health, environmental degradation, and current land use). The overlap between different categories provided an understanding of availability and spatial distribution of marginal lands in Nebraska. Emery et al., (2017) also employed an overlay analysis of numerous secondary data sources to assess the variation in marginal lands in the US. Depending on the land cover data sources, the authors observed a variation in total marginal land coverage across the US, ranging from 26.7 MHa. To 58.9 -MHa. Cai et al., (2011) utilizes fuzzy logic modelling to identify the availability of marginal lands. Fuzzy logic modelling acknowledges the uncertainties of land use data sets and categorizes the land classification to address this variability. Jiang et al. (2021) use remotely sensed time-series land cover data to identify the transition between croplands and non-crop lands. The authors hypothesize this transitional land cover as marginal land and define these croplands in transition with uncertainty. This research is restricted to identifying marginal lands based on economic aspects. The findings show approximately 58.3 MHa. of marginal lands across the USA. Table 2.2 summarizes specific methods adopted by different scholars to identify/delineate marginal lands across the world.

Table 2.2: Quantification of Marginal Lands across the USA

References	Method	Study Area	Area in MHa
Baxter & Calvert (2017)	Quantitative logic set	USA	4.9 - 15
Gopalakrishnan, et al. (2011)	Overlay GIS analysis	Nebraska, USA	N/A
Emery, et al. (2017)	Overlay GIS analysis	USA	58.9 - 126.7
Cai, et al. (2011)	Fuzzy Logic Modeling	USA	N/A
Kang, et al. (2013)	Overlay GIS analysis	USA	N/A
Jiang, et al. (2021)	Remotely sensed time-series land cover data analysis	USA	58.3
Milbrandt, et al. (2014)	Overlay analysis	USA	86.5

2.3 Materials and Methods

2.3.1 Study area

Kansas is a landlocked state with a total land area of approx. 81,759 sq mi or 211, 754 km² and is ranked as the fifteenth largest area of the U.S. by state (Geography, 2020). It is bordered by Colorado to the west, Nebraska to the north, Missouri to the east and Oklahoma to the south (Figure 2.3). With 105 counties and 628 cities, the population of Kansas has reached 2,940,865 in 2020 (US Census Bureau, 2020). This Central Great Plain state has varying topography with most of the western part having a flat or undulating surface, while the eastern part has hills and forest. However, the elevation increases gradually from east to west (US Geological Survey). This state falls under three climates: humid continental, semi-arid steppe, and humid subtropical as classified by Köppen climate classification. The summer temperature of these three climatic regions varies from 80 °F to more than 100 °F (Kansas, 2020). According to the Weather Data Library of Kansas State University, total precipitation varies from 45 inches

or more in southeastern Kansas to less than 18 inches in southwestern Kansas. The Great Plain states (including Kansas) have a moderate to high GHI (Global Horizontal Irradiation) and photovoltaic power potential among the USA states (National Renewable Energy Laboratory). According to the Kansas Department of Agriculture (2016a) approximately 87% of Kansas is devoted to agriculture, which significantly contributes to the state's economy. In addition to this solar potential, a significant amount of land, approximately 1,898,705 acres of land are under CRP (Conservation Reserve Program, 2022) that are unsuitable for agricultural production (EWG conservation Database). Researchers have termed these CRP lands as marginal land and identified them as a potential alternative for installing SPV (Wells et al., 2003).

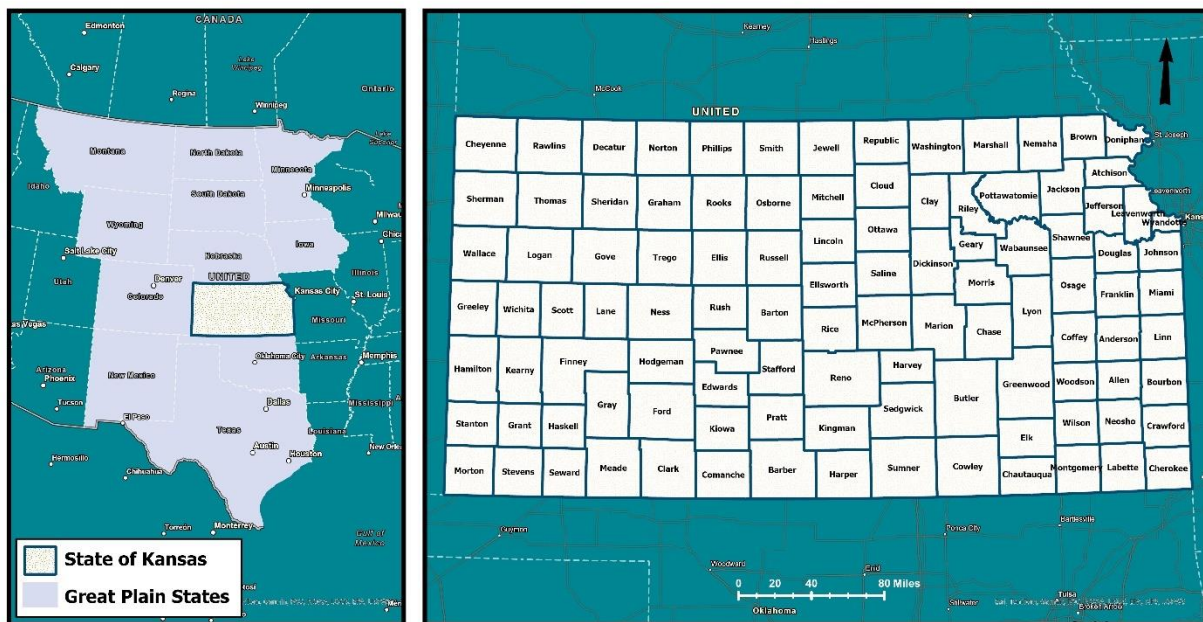


Figure 2.3: Study area: State of Kansas

2.3.2 Quantifying Marginal Lands within Kansas

Previous research that has been conducted on quantifying marginal lands can be categorized under two broad foci: (1) *Marginal land focusing on bio-energy crop productivity* and (2) *Generalized Marginal land*. Marginal lands focusing on bio-energy crop productivity

extensively depends on biophysical, chemical, environmental, and economic properties of the soil. However, researchers have emphasized soil biophysical properties as one of the most significant criteria in identifying marginal lands (Jiang et al., 2019; Gopalakrishnan et al., 2011). *Generalized marginal land* focuses on the biophysical properties of soil, for instance, slope, susceptibility to erosion, drainage capacity, flood frequency, and so forth (see Appendix A). Nonetheless, some researchers have utilized specific land cover directly in their analysis, for instance, fallow land, abandoned land, and CRP (Conservation Reserve Program) lands. I have utilized both of these broad criteria to develop a framework to identify marginal lands in Kansas.

My research examines utilizing marginal lands for deploying solar photovoltaics. Thus, I focus on criteria that contribute the most into my end goal. For instance, soil erosion, drainage density, flood occurrence, slope, barren land cover, non-prime farmlands, and specific soil groups based on their potential for agriculture and other usage (Land capability classes) that are efficient in delineating marginal lands.

Researchers have used a common set of criteria to quantify marginal lands. These criteria can be based on biophysical criteria and specific land cover types. By combining both criteria, I developed a framework to identify the marginal lands for Kansas. Figure 2.4 provides an understanding of the criteria that I utilize to define marginal lands. While defining marginal lands, I consider four biophysical criteria: soil erosion, flood duration, slope, and drainage capacity and four land cover criteria: Conservation Reserve Program lands, barren land cover, non-prime farmlands, and specific soil groups based on their productivity (land capability classes). Based on these criteria I define marginal lands as;

“Unproductive and underutilized land cover encompassing barren land, Conservation Reserve Program land, non-prime farmland that may or may not contain critical biophysical

conditions such as, high erodibility, high flood frequency, steep slopes, and poor drainage capacity.”

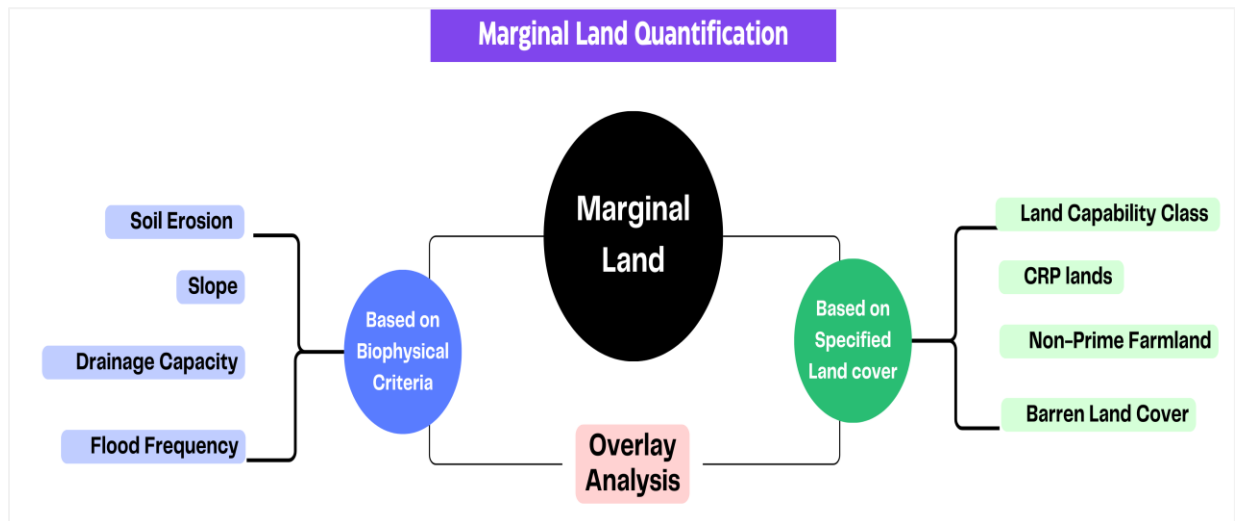


Figure 2.4: A methodology to quantify marginal lands.

2.3.3 Data Sources

I have utilized numerous data sources that have been previously adopted by researchers in defining and quantifying marginal lands (Gopalakrishnan et al., 2011; Kang et al., 2012; Emery, et al., 2017; Milbrandt et al., 2014). Despite having errors in remotely sensed data, researchers have widely adopted this method in quantifying marginal lands (Gopalakrishnan, et al., 2011). A major portion of this quantitative analysis relies on remotely sensed satellite imagery. These satellite images from varied sources have been processed in ArcGIS Pro 3.1.3 platform to generate maps showing the distribution of marginal lands within the State of Kansas.

The Gridded Soil Survey Geographic Database or gSSURGO, developed by United States Department of Agriculture (USDA) Natural Resources Conservation Service (NRCS) has been employed to obtain data pertinent to marginal land criteria. This database contains comprehensive “taxonomic classification of each soil series in the United States, Territories,

Commonwealth, and Island Nations served by USDA-NRCS” in the form of Environmental Systems Research Institute, Inc. (ESRI) file geodatabase (Soil Survey Staff, 2020). The soil data are stored in separate shapefiles with distinct soil attributes in tables. The gSSURGO data is based on traditional vector-based data; however, represented as a raster layer with a 30m cell size. Each of these raster cells are linked to their attribute table through a unique identifier known as a map unit key. Map unit is the smallest unit with an area encompassing 617 hectares or 1544 acres of land area. Each map unit represents areas identified by similar soil types or specific areas on the ground. These map units are used in soil surveys to classify and map the distribution of soils on the landscape. In my thesis, I obtained data from gSSURGO for (1) soil drainage capacity: poorly drained and very poorly drained, (2) soil erosion: erosion class 2,3, and 4, (3) land capability classes: Class 5, 6, and 7, (4) non-prime farmlands, and (5) flood occurrence: at least 5%-50% chances of flooding in a year. The attributes related to each of these criteria are linked to map units and the thresholds for the criteria are chosen based on the existing literature.

Barren/idle land cover data has been collected from the USDA NASS Cropland Data Layer (CDL), a raster data with spatial resolution of 30m. This dataset provides crop-specific categorized geo-spatial information. Lastly, the Conservation Reserve Program land data was collected from USDA FSA (United States Department of Agriculture Food Service Agency). Data related to slope information has been acquired from U.S. Geological Survey. Table 2.3 gathers information on major criteria considered in quantifying marginal lands, the annotated variables, their thresholds, and supporting references.

The GIS software ArcGIS Pro was utilized to produce maps that portray the distribution of marginal lands based on selected criteria. Moreover, an overlay analysis is conducted in

ArcGIS pro to show possible overlap of two or more criteria. The maps and associated areas were also determined in ArcGIS Pro platform.

I used Common Land Unit boundaries to delineate marginal land. The CLU boundary data has been derived from USDA FSA (Farm Service Agency). The major purpose of utilizing CLU boundaries as spatial scale of accuracy assessment is twofold; (a) CLUs are the smallest spatial scale for geospatial analysis, and (b) these boundaries represent common land cover and land management (Freeman, 2022). Thus, to select the most accurate and most suitable marginal lands for solar photovoltaics, I utilized CLU boundaries.

Table 2.3: List of criteria, reference, and spatial resolution.

Marginality Criteria	Variables	Threshold	Data Sources	Reference
Soil Biophysical Criteria	Slope	Greater than 5%	USGS 1/3 arc-second DEM	Gopalakrishnan et al., 2011
	Soil erosion	Class 2,3, and 4	gSSURGO	Gopalakrishnan et al., 2011; Kang et al., 2012
	Flood duration	At least 5%-50% chances of flooding in a year	gSSURGO	Kang et al., 2013; Gopalakrishnan et al., 2011
	Drainage	(a) poorly drained, and (b)very poorly drained	gSSURGO	Gopalakrishnan et al., 2011
Landcover Based Classification	CRP	Land cover	USDA FSA	Emery, et al., 2017; Gopalakrishnan et al., 2011
	LCC	LCC (class 5 to 7)	gSSURGO	Emery, et al., 2017
	Barren/Idle Land cover	Land cover that has been barren/fallow for at least four years	USDA NASS Cropland Data Layer (CDL)	Milbrandt et al., 2014
	Non- prime Farmland	Land cover that avoids statewide and locally important and unique farmlands.	gSSURGO	

2.3.4 Soil Biophysical Criteria

2.3.4.1 Soil erosion Criteria

Soil erosion is a crucial parameter in defining marginal land as it determines land productivity and suitability for specific land uses (Gopalkrishnan et al., 2011). Soil erosion is one of the most important factors that has both direct and indirect impacts on other properties of soil, such as, soil productivity, water retention capability, and infiltration capability (Morgan, 2009). Soil erosion tends to deteriorate the soil structure and results in the removal of the most fertile and nutrient-rich topsoil. This topsoil loss significantly impedes the key functions performed by soil, supporting plant growth and food production, soil water retention, storage of nutrients, and providing habitat to microorganisms (Zachar, 2011). Thus, lands with severe soil erosion are often considered marginal as it requires extensive and expensive management to maintain their viability for other land use purposes (Jiang et al., 2019; Gopalakrishnan et al., 2011; Kang et al., 2012). I used SSURGO soil erosion data in our framework and separated highly eroded soil cover from more productive soil cover. SSURGO soil data have five distinct classes for soil erosion,

None: Area of soil deposition.

Class 1: Represents topsoil erosion percentage ranging from 1% to 25%.

Class 2: Represents topsoil erosion percentage ranging from 25% to 75%.

Class 3: Represents topsoil erosion percentage ranging from 75% to 99%.

Class 4: In this map unit, all of the original topsoil has been lost to erosion.

Following previous literature, I chose all soil cover under class 2 to 4 as marginal land for our analysis. Figure 2.5 shows the distribution of eroded and non-eroded land cover classes within the state of Kansas.

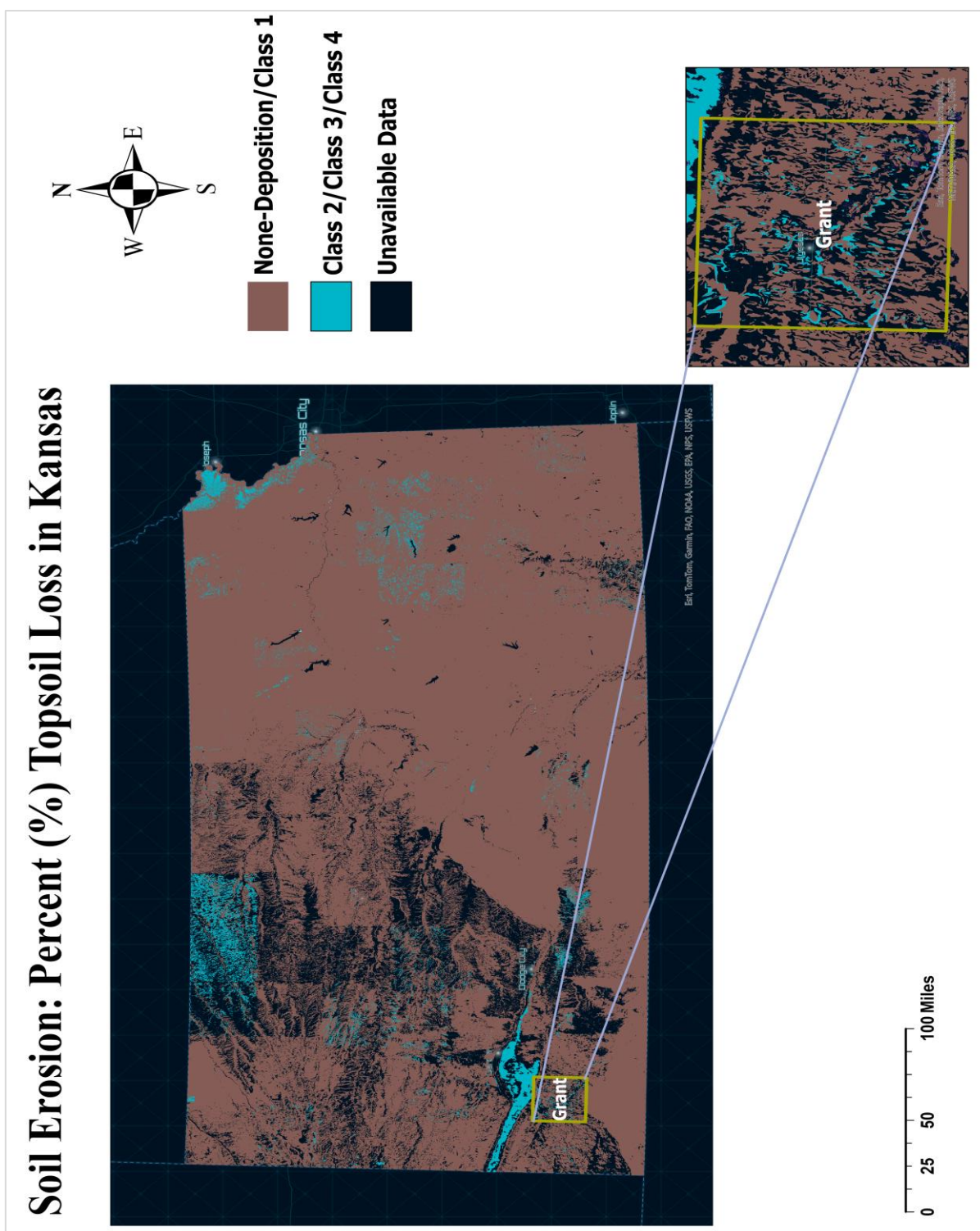


Figure 2.5: Soil erosion classification.

2.3.4.2 Soil Drainage Criteria

Drainage plays role in crop production and agriculture. Soils with poor drainage capacity tend to retain excess water, leading to waterlogging (Valipour, 2014). Waterlogged soil becomes anaerobic, meaning it lacks oxygen, which is necessary for root respiration and healthy plant growth. Moreover, prolonged waterlogging can damage plant roots, reducing crop yields, and making the land less suitable for agriculture. (Manik et al., 2019). Furthermore, poor drainage can enhance soil salinity, which can limit crop productivity (Valipour, 2014). Properly drained soils are less likely to lose nutrients through leaching, which can occur when excess water washes nutrients away from the root zone. Gopalakrishnan et al. (2011) defined marginal land as poorly and very poorly drained parcel of lands.

SSURGO data has classified drainage capacity for soils into 8 classes: (1) excessively drained, (2) somewhat excessively drained, (3) well drained, (4) moderately well drained, (5) somewhat poorly drained, (6) poorly drained, (7) very poorly drained, and (8) subaqueous soils. In poorly drained sites, the water is removed so slowly, resulting in a shallow water table (approximately 1 foot). However, occasionally wet soil can be found very near to the surface. On the contrary, soil with very poor drainage capacity usually has a wet surface and a water table less than 1 foot in depth. Both classes are unsuitable for crop production. I selected 3 types of soil drainage classes; (a) somewhat poorly drained, (b) poorly drained, and (c) very poorly drained to identify potential marginal lands. Figure 2.6 depicts a map showing the drainage conditions required to be classified as marginal land.

Soil Drainage Capacity in Kansas

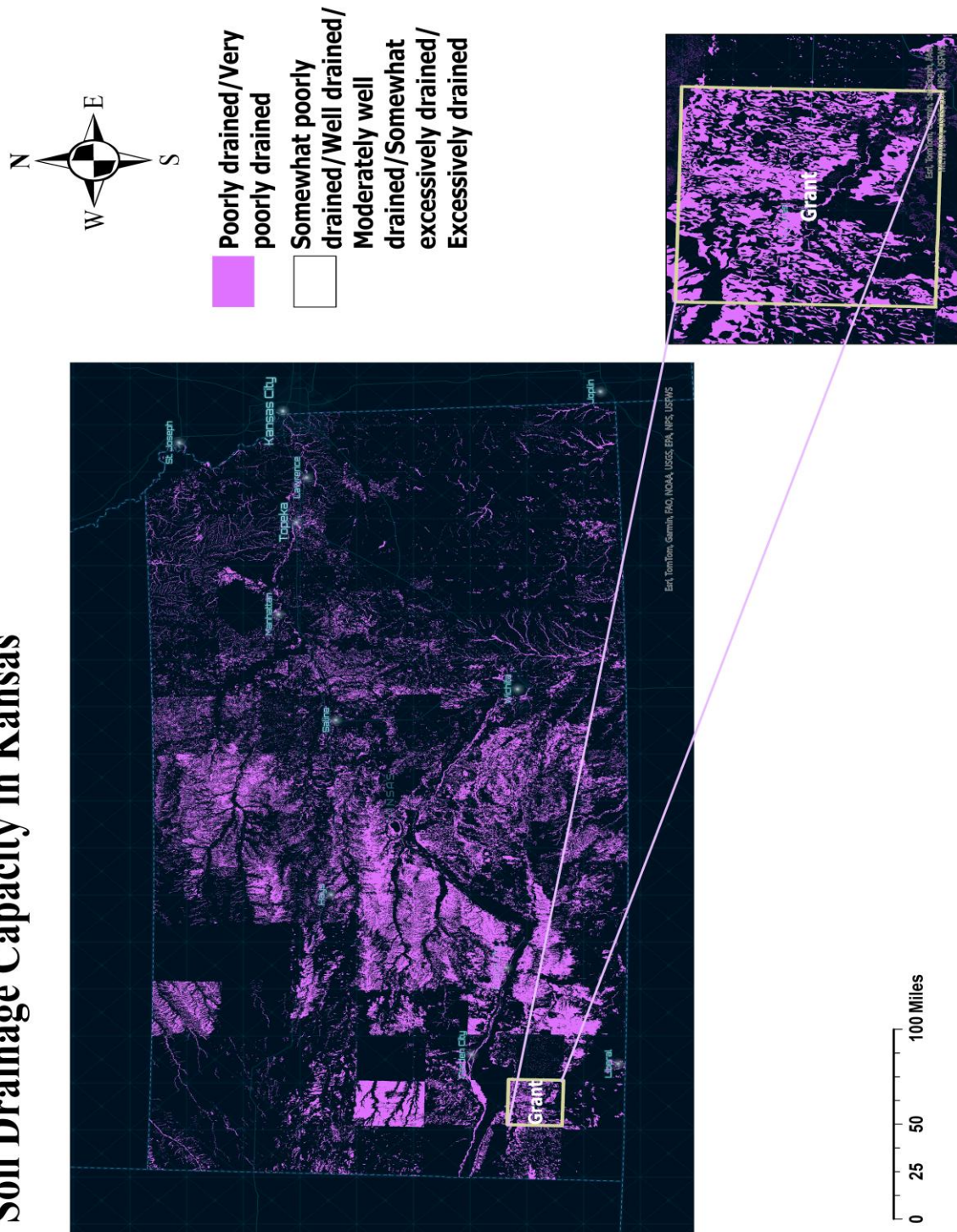
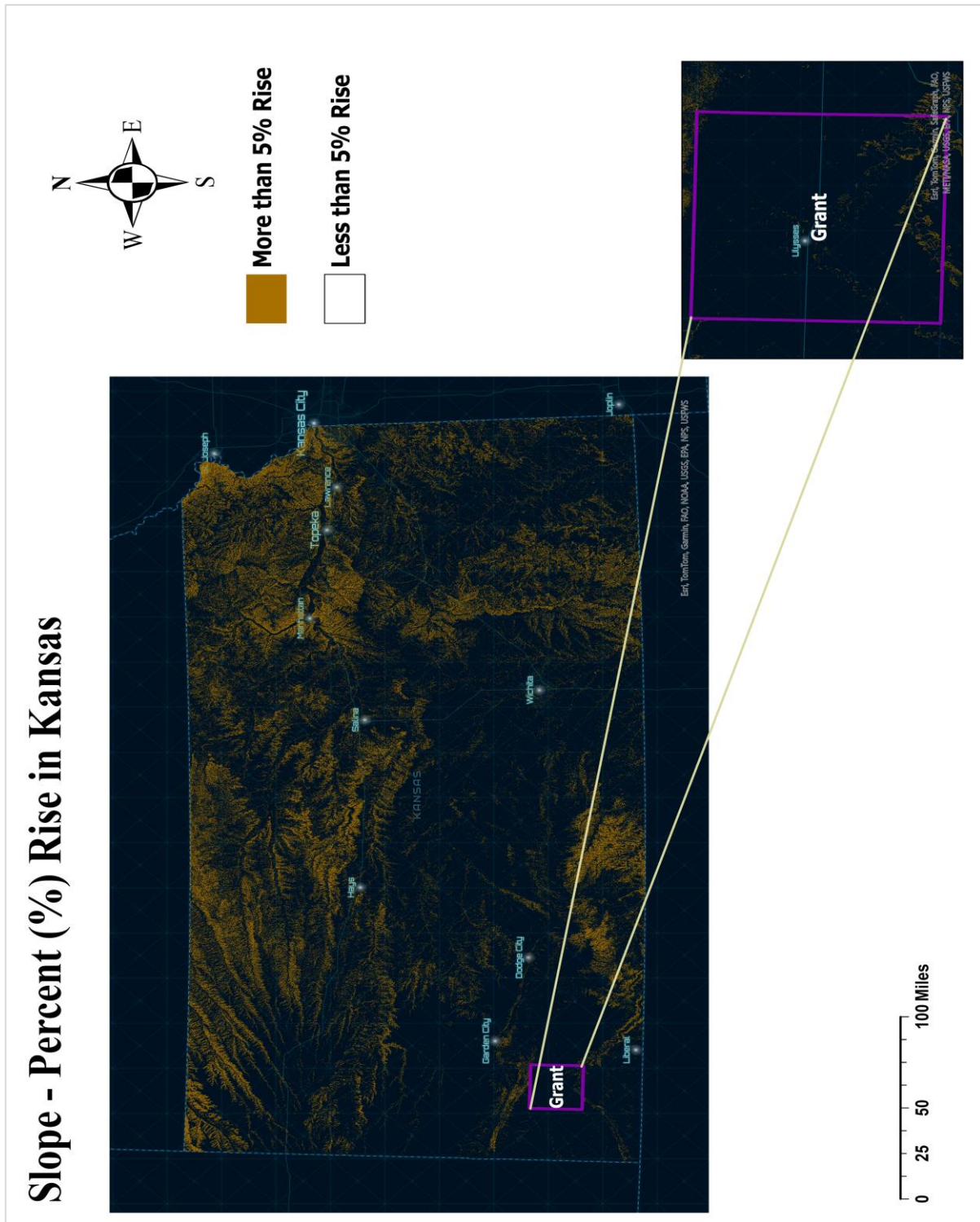


Figure 2.6: Soil drainage density distribution.

2.3.4.3 Slope Criteria

Lands with steep slopes are generally considered marginal for crop production. Steep slopes can lead to various problems, such as soil erosion, water runoff, and difficulty in conducting mechanized farming operations. Moreover, steeper slopes are more prone to soil erosion, which can result in the loss of topsoil, nutrients, and overall soil fertility. Furthermore, the slope of the land can also impact soil quality. Water tends to drain more rapidly on sloping land, potentially leading to reduced water retention and availability for crops. Considering the fact that more than 80% of landcover in Kansas is flatland, for this study, I have selected all landcover greater than 5% rise for classifying marginal land. (Figure 2.7).



2.3.4.4 Flood Frequency Criteria

Researchers have focused on flood-prone areas as an indicator of marginal lands (Kang et al., 2013; Gopalakrishnan et al., 2011). Gopalakrishnan et al. (2011) identified areas with frequent flooding as marginal land. Flood frequency provides information regarding the size and regularity of flood occurrence that is derived from the historical record of yearly peak water discharge. I utilized gSSURGO flood frequency classification system and categorized areas with frequent and occasional flood frequency as marginal land. The class “frequent” portrays areas that have more than a 50% chance of flooding in any year. While the “occasionally” flooded regions have 5% to 50% chances of flooding in any year. The areas with rare and very rare flood frequency are those where flooding is very unlikely or highly contingent on unusual weather conditions. In this study, I reclassified the food occurrence in Kansas into two categories: (a) none/rare/very rare and (b) occasional/frequent classes. Regions identified with occasional and frequent flooding are used to classify marginal lands and are shown in Figure 2.8.

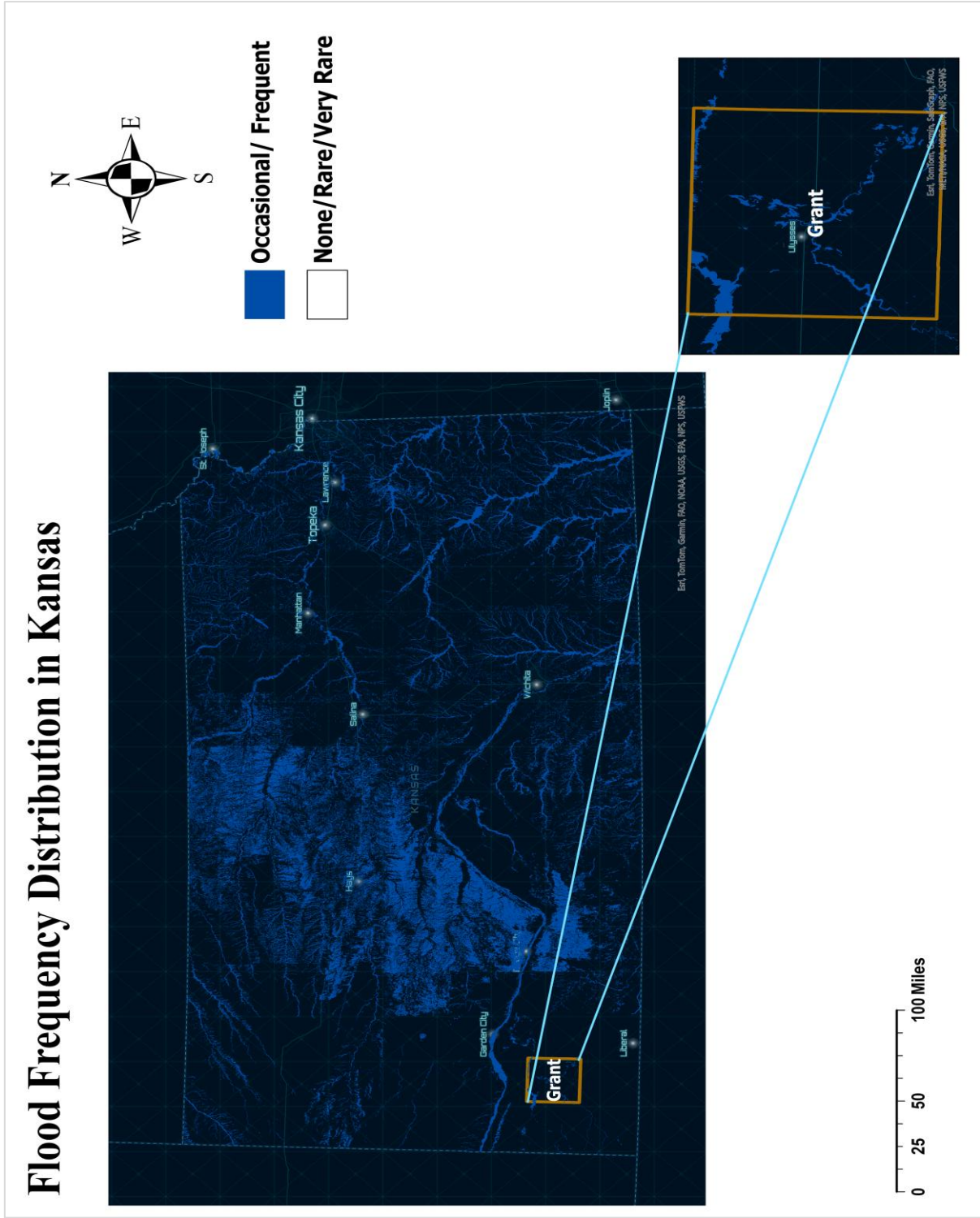


Figure 2.8: Distribution of flood frequency classes within the State of Kansas

2.3.5 Land cover-based classification Criteria

2.3.5.1 Land capability classes

Land capability classes (LCC) are used to categorize land covers based on their suitability for growing crops (United States Department of Agriculture, Soil Conservation Service, 1961). These classes include distinct soil types based on soil pH, texture, depth, slope, and so forth. Land capability classes from Classes from I to IV are considered most suitable for growing crops, whereas classes V – VII are not suitable for croplands. These classes (V – VII) are mostly utilized for grazing, pasturelands, wildlife, recreation, and aesthetic purposes. Classes used for classifying marginal lands include:

LCC 5: These soils are relatively resistant to erosion but face specific challenges that limit their optimal use to areas like pastures, rangelands, forests, or regions designated for wildlife.

LCC 6: These soils present notable restrictions, typically rendering them unsuitable for agricultural cultivation, but suitable for pastures, rangelands, forests, or wildlife zones.

LCC 7: Characterized by stringent limitations, these soils are deemed non-viable for agriculture and are best suited for grazing territories, woodland areas, or wildlife refuges.

I utilized this USGS Soil Survey Geographic (SSURGO) database to identify specific land capability classes that represent marginal lands. By comparing LCC to USDA National Land Cover Data layer, my research has identified LCC classes 5 to 7 complementing marginal lands. To analyze this, I overlayed the CDL-2022 land cover data and SSURGO LLC data. Before conducting the overlay procedure, I reclassified the CDL data into 6 distinct classes- Crop/Vegetation, Barren/Idle, waterbodies, Woodland, Developed area, and Herbaceous/Grassland cover. After correlating the CDL data with the LCC classes it is evident that most of the area of LCC classes 5 to 7 falls onto Barren/Fallow, herbaceous, and Shrubland

cover (Figure 2.9). In Figure 2.9, a stacked bar chart is utilized to illustrate the distribution of various land capability classes across different types of land cover, with each bar segment indicating the proportion of each class within the total composition for that land cover type.

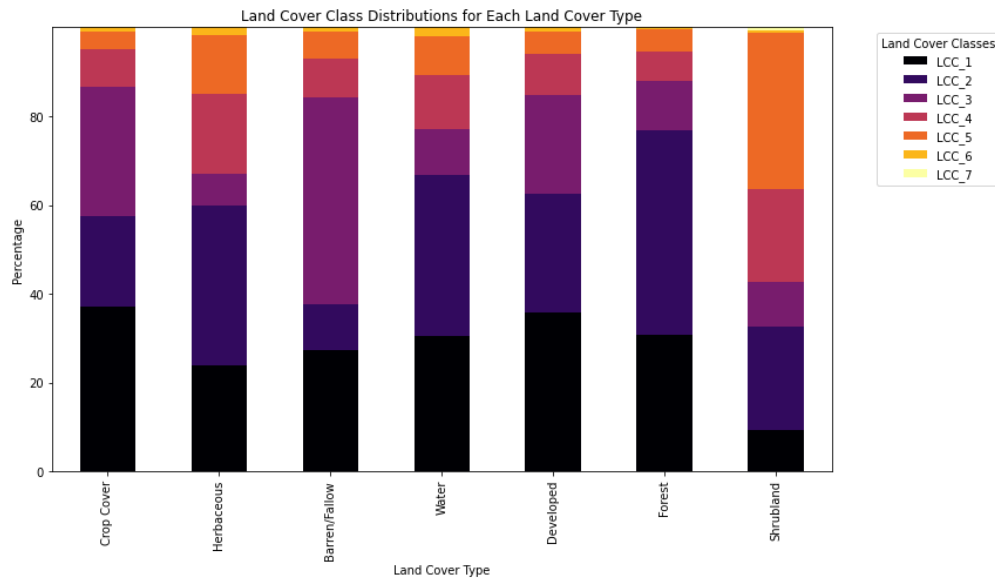


Figure 2.9: Correlating land capability classes with Cropland Data Layer (CDL) data.

My analysis coincides with previous research conducted on quantifying marginal lands. For instance, Hamdar (1999) and Gelfand et al. (2013) have considered land capability classes 5 to 7 as marginal land cover. Thus, moving forward, I will employ Land Capability Classes 5 through 7 to delineate marginal land covers in Kansas. The processing provided a binary raster, 0 indicating unsuitable LCC and 1 indicating suitable LCC, as shown in Figure 2.10.

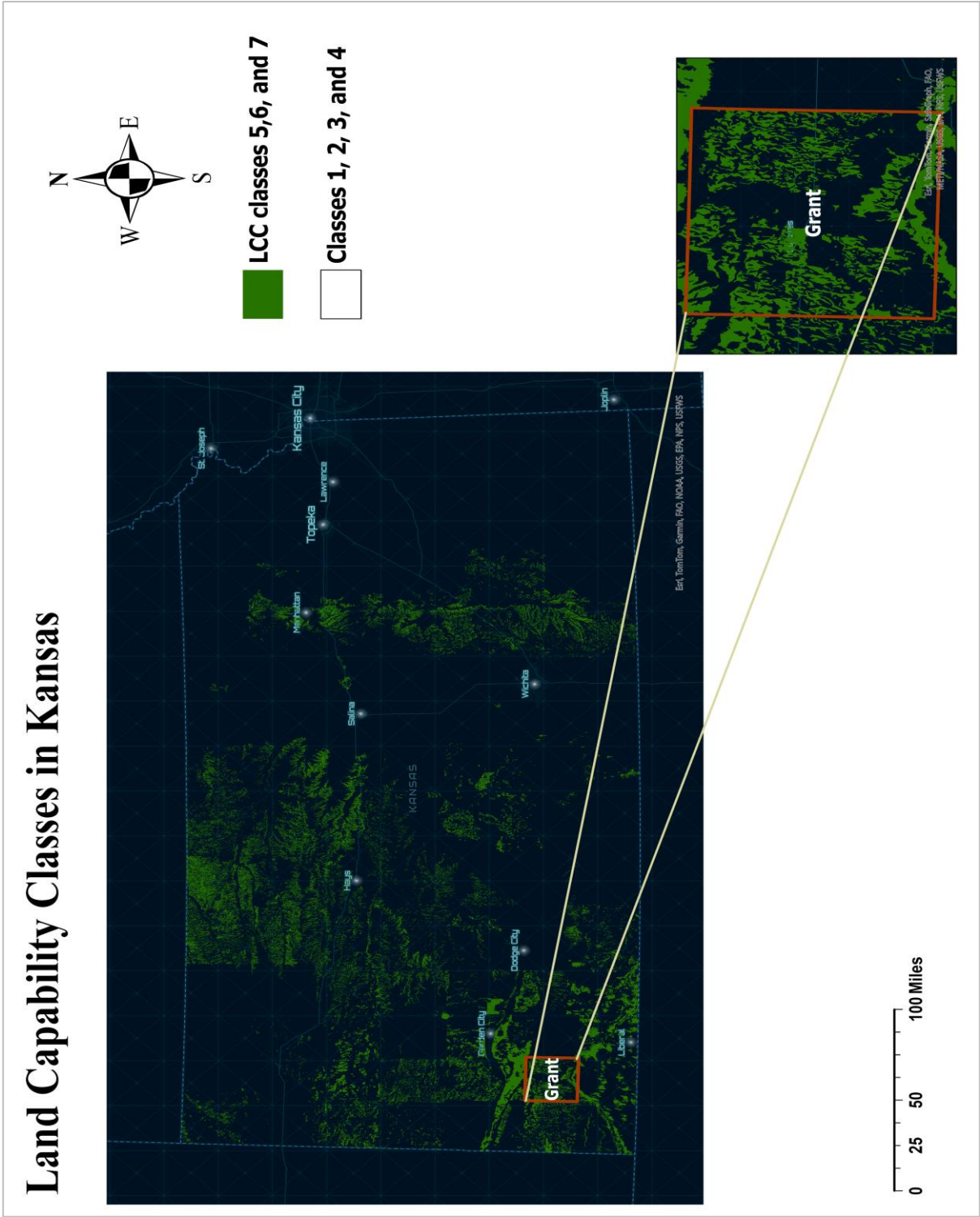


Figure 2.10: Distribution of marginal LCC classes within Kansas

2.3.5.2 Barren Lands

According to the USDA Economic Research Service (ERS) idle cropland or fallow lands are land parcels that are not utilized for cultivation or vegetation growth. In most cases this restriction on use arises from the physical and economic condition of those land covers, for instance low soil fertility, harsh environmental conditions, limited water resources, and so forth. Gopalakrishnan et al., (2011), Campbell et al., (2008) and Milbrandt & Overend (2009) have employed idle or fallow land in identifying marginal lands. While quantifying marginal land based on economic aspects of land cover, Jiang et al. (2021) posited that when a cropland cover remains uncultivated for at least four years, it can be defined as barren land. I adopted the analysis of Jiang et al. (2021) to identify barren land cover in Kansas which is provided in Appendix B.1.

CDL data contains extensive information on land cover type data that has been developed by utilizing extensive machine learning algorithms, with a spatial resolution of 30m. Thus, I utilized the CDL to identify barren and idle/fallow land cover within Kansas. Barren pixel remains unused for production over a period of 4+ years can be defined as barren land cover (including the idle/fallow land cover under the broad ‘Barren’ land cover category). For this time series analysis, I selected years 2019, 2020, 2021, and 2022 and examined the changes in barren and idle/fallow land covers in Kansas. After identifying pixels that remained constant as barren and idle/fallow land cover over the period of 2019 to 2022, I reclassified these two land covers as “Barren” lands. According to the assessment, the total barren land that remained constant over the 4 years of timespan is 0.037 million hectares or 90,561.76 acres. The classification from geospatial processing is portrayed in Figure 2.11.

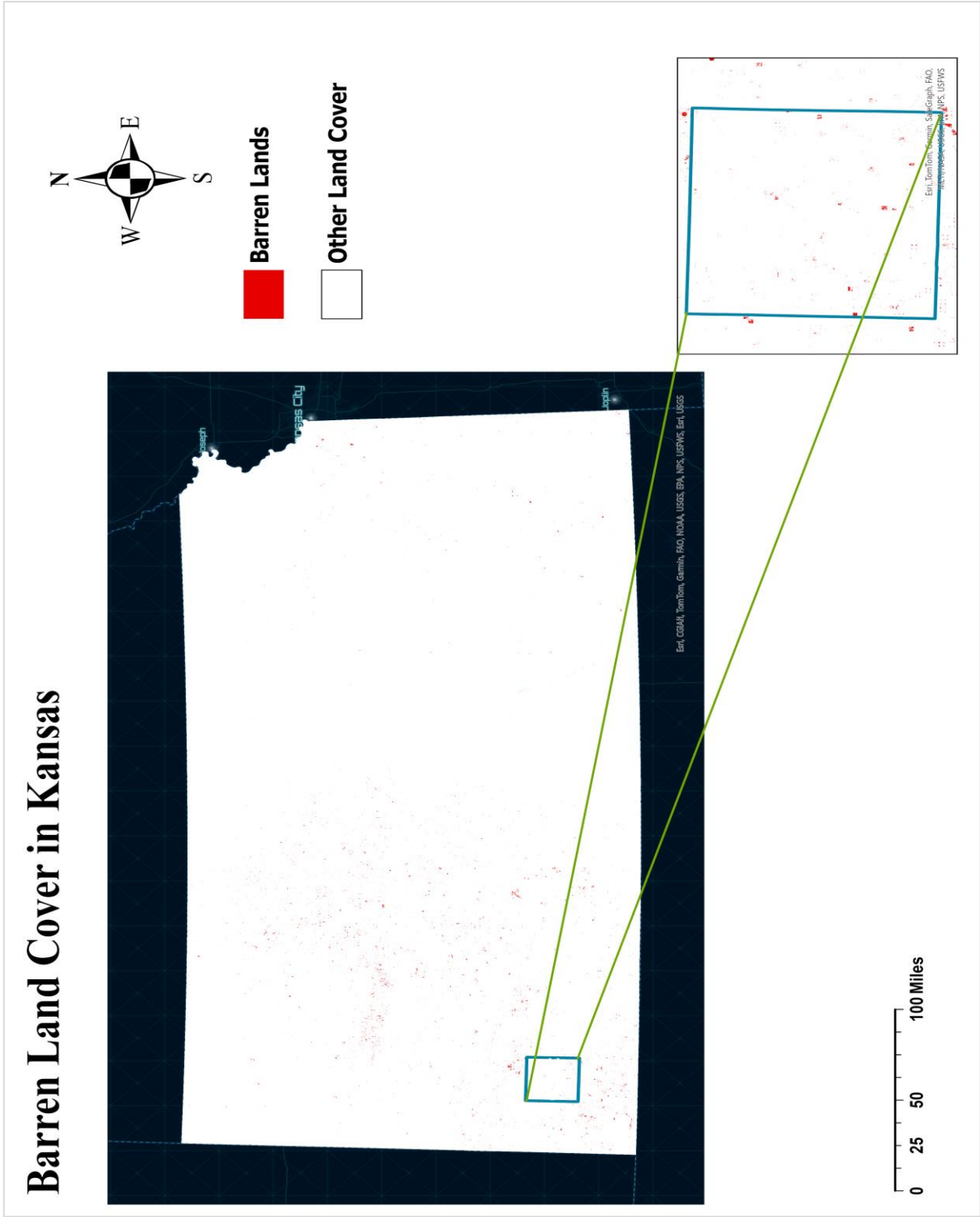


Figure 2.11: Barren land cover in Kansas.

2.3.5.3 Non-Prime Farmland

To protect high quality agricultural land cover the Farmland Protection Act (1981) intends to limit the conversion of productive farmlands to other uses. This Act results in identifying high quality agricultural land cover as prime farmlands, unique farmlands, and land of statewide or local importance (Natural Resource Conservation Service). These farmlands are utilized for production of food, fiber, forage, and other fruits and vegetables. The SSURGO soil database identifies land cover that is considered non-prime farmlands. According to the SSURGO soil database, farmlands that don't meet the criteria of productive farmlands, can be considered as non-prime farmlands. To separate this non-prime farmland, the prime, unique, and important (state and local) farmlands were eliminated. The output of this processing provides an estimation of 4.03 MHa. of non-prime farmlands in Kansas (Figure 2.12).

2.3.5.4 CRP (Conservation Reserve Program)

The Conservation Reserve Program is the largest private land conservation program that is administered by the US Farm Service Agency with a goal of conserving environmentally sensitive landcover to achieve sustainability. The CRP program simultaneously aims at improving water quality (Cullum et al., 2010; Lowrance et al., 2002), improving soil health and restoring habitats (Ciuzio et al., 2013; DiGaudio et al., 2015; Higgins et al., 2002), and sequestering carbon (Li et al., 2017). According to USDA Farm Service agency (2023), CRP lands covered approximately 24.80 million acres of land. In Kansas, the total area of land under the Conservation Reserve Program (CRP) is approximately 1.976 million acres. Under the CRP program, farmers receive an annual payment in return for removing all eroded and sensitive landcover from agricultural production (Lubben & Pease, 2014).

I collected CRP land cover data from the USDA Farm Service Agency under a specific MOU with Kansas State University, spanning from 2012 to 2021. These CRP land cover data have been processed and analyzed to produce a dataset that includes cumulative CRP land cover from 2012 to 2021. CRP contracts typically lasts 10 to 15 years, thus merging CRP land cover from 2012 to 2021 covers a complete contract cycle and ensures a comprehensive inclusion of CRP land cover/marginal lands. Furthermore, my goal is to employ this comprehensive CRP land cover data to help validate the model produced by my framework. This necessitates the inclusion of CRP landcover in a complete cycle. According to my research findings, Kansas has approximately 1.15 million hectares (approx. 2.84 million acres) of land cover under the Conservation Reserve Program (CRP). Appendix B.2 provides the flowchart illustrating the steps taken to process the CRP land cover data over 10 years. Subsequently, Figure 2.13 illustrates a map that delineates the extent of land cover enrolled in the Conservation Reserve Program,

spanning from 2012 to 2021. This dataset will be utilized to assess the accuracy of the produced marginal land cover for the state of Kansas.

Conservation Reserve Program Lands in Kansas

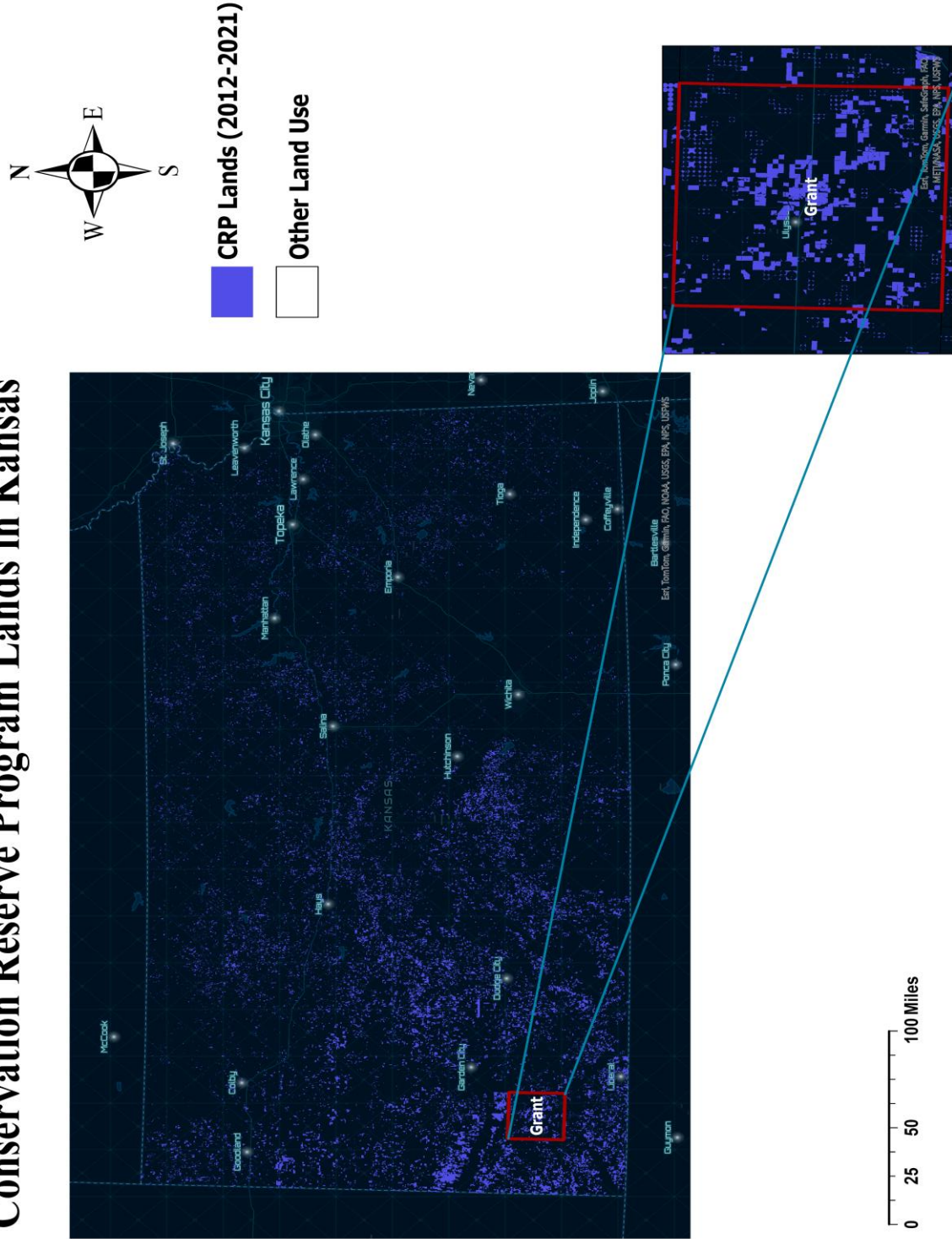


Figure 2.13: Conservation Reserve program (2012-2021)

2.3.6 Delineating Marginal Lands, accuracy assessment and validation

Following the framework described in section 2.3.2, I have utilized both the biophysical and land cover criteria to delineate the distribution of marginal lands in Kansas. A conditional geospatial analysis was conducted to identify marginal land covers that fulfill both biophysical and land cover criteria. The geospatial tool “Raster Calculator” in the ArcGIS Pro interface was utilized to identify marginality of Kansas depending on the presence/absence of certain land cover and soil biophysical criteria. The methodology to conduct this conditional analysis is described under section 2.3.6.1 (Step 01).

While this analysis provides an overview of the distribution of marginal lands, there still contains some uncertainty over the accuracy of identified marginal land, as most of the selected criteria are derived from satellite images (Congalton and Green, 2019; Congalton, 1991). Thus, my aim is to assess the accuracy of marginal land cover in Kansas by utilizing CRP as ground truth data. These CRP land covers are assumed as marginal land due to their biophysical, economic, and environmental limitations, which allow them to potentially serve as a reliable and accurate ground truth dataset. Researchers such as Gopalakrishnan et al., 2011 and Emery et al., 2017 have considered CRP land cover as marginal land cover. By identifying CRPs that fulfill the requirement of marginality, I will provide a novel approach to validate marginal lands in Kansas. By following this novel approach, I aim to answer the following questions: (1) What percentage of CRP lands are correctly classified as marginal lands? (2) What percentage of CRP lands are correctly classified as non-marginal lands? and (3) What is the error rate in both of these analyses? By identifying CRPs that fulfill the requirement of marginality, I will provide a novel approach to validate marginal lands in Kansas.

2.3.6.1 Analyzing marginality of Kansas

The process of identifying and validating marginal land in Kansas encompasses two major steps. An overlay analysis has been conducted by excluding CRP land cover from the overlay analysis. The process of excluding CRP land cover from overlay analysis is considered as the preliminary assessment of marginal land that will be validated by CRP land cover.

Step 1: Marginality Assessment excluding CRP lands

Researchers have used different values of thresholds to delineate marginal land when conducting overlay analysis. To reduce uncertainty, we have provided the possible ranges of marginal land areas within Kansas. In this particular analysis, I aim at classifying land into different levels of marginality depending on how many of the eight specified criteria are met. The criteria used in this method are a mix of biophysical features and land cover types. The ‘**Con**’ (short for "conditional") statements are used to check the sum of the criteria met at each pixel and then classify the pixel into categories based on these sums.

For this first stage, we have excluded CRP land cover from our analysis and the rest of the criteria were processed to integrate in an overlay analysis. An overview of methods and tools utilized to conduct this analysis is provided in Appendix B.3.

To initiate the overlay analysis, we have converted all raster layers into a binary format employing ArcGIS Pro. For this preliminary step we have excluded Conservation Program Land cover and overlaid seven of our selected criteria. The methodology is hinged on utilizing the Conditional operation to set precise parameters for raster cells, ensuring a targeted approach to the analysis. Our aim is to employ these conditions as a foundation for systematically identifying and quantifying areas of marginal land cover. To capture a range of scenarios, we have defined and applied three distinct conditional operations across the reclassified raster layers. These

operations enabled us to classify areas according to their cumulative environmental characteristics, as follows:

- **High Marginality:** This condition identifies areas with a high degree of marginality where a majority of the criteria are present. According to this condition, at least five criteria must overlap to consider a pixel marginal land.
- **Moderate Marginality:** This operation was designed to recognize areas that exhibit a concentration of at least three or more biophysical or landcover criteria.
- **General Marginality:** The broadest condition, capturing any pixel exhibiting at least one of the criteria. This condition provides an inclusive overview of lands with any degree of limitation, ensuring that all potentially marginal areas are considered for further analysis or intervention. For our further analysis we will be utilizing this conditional operation to quantify marginal land.

For the purposes of further analysis, I will be utilizing the least stringent approach, classifying a land cover as marginal land if it meets at least one criterion. By adopting this condition, I attempt to include all land cover that shows at least one attribute of marginality.

Step 2: Exclusion of Restriction Criteria

At this step, I removed all land covers containing wetlands, urban areas, and forest cover from the selected marginal land layer (land cover that meets at least one criteria). By omitting wetlands, urban areas, and forests from our dataset, I refine the analysis to remove regions intrinsically unsuitable for classification as marginal land, owing to environmental protections, urban development, or the ecological significance of forests. Moreover, the exclusion of these land covers ensures a more accurate identification of truly marginal agricultural lands. Lastly, I

converted the resultant marginal land raster layer into binary raster, 0 indicating absence and 1 indicating presence of marginal land pixels.

2.3.6.2 *Scaling and Thresholding*

The major concern of accuracy assessment lies in identifying suitable scale to validate the model produced. To provide more insights into the output and to validate it, I employed CLU or Common Land Unit Boundary as our study scale. The Farm Service Agency defined Common Land Unit (CLU) as “A contiguous farmland parcels distinguished by a stable boundary, homogeneous land cover and management, and typically under unified ownership or associated with a particular producer group”. These boundaries are used for (a) creating a database for land unit boundaries and linking it to other data sources, (b) providing more accurate land measurement, (c) summarizing agricultural land cover information at small county, state, or national level, and so on.

In GIS interface, these land boundaries are used for high quality analysis by linking them to other information, to make better decisions. These boundaries provide information regarding current land management, land use, and property boundaries. Thus, I chose CLU as the spatial scale of aggregation process.

Moving forward with the CLU-based geospatial analysis, I adopted a thresholding method to identify CLUs that contain (a) marginal lands, (b) non-marginal lands, (c) CRP lands, and (d) non-CRP lands. The thresholding technique will convert all land cover data into large scale (from 30m spatial resolution) and help simplify the validation process as well as enhance accuracy of marginal land cover. I will assess the accuracy of marginal lands under three thresholds; (a) at least 25% or (b) at least 50% or (c) at least 75%, where each threshold will

identify CLUs based on the percentage of landcover (marginal lands and non-marginal lands) present inside each unit of CLU (Figure 2.14).

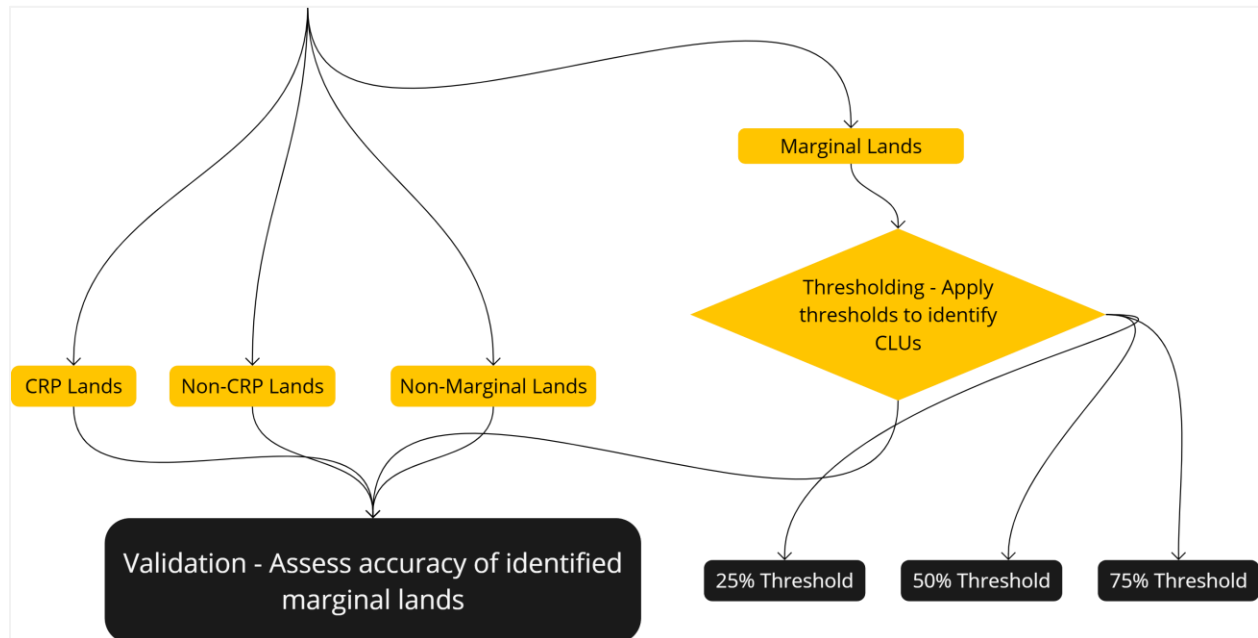


Figure 2.14: Process of downscaling land cover data for accuracy assessment and validation

Aggregating marginal lands

With an aim to assess the accuracy of marginal lands, an aggregation approach was utilized. This aggregation process selects CLU polygons containing marginal land pixels based on certain threshold values, such as (a) at least 25%, (b) at least 50%, or (c) at least 75%. This rule helps identify CLU polygons by calculating the amount (threshold or percentage) of marginal lands that falls into the CLU boundaries. This method effectively identifies CLUs that can be classified as marginal lands.

Aggregating CRP lands

The next focus is to identify CRP land cover for CLU boundaries. In this way, the CRP land cover can be compared with the same scale of marginal land cover. An “intersection” method was employed to calculate CLU boundaries that contain CRP land cover. This step is crucial for validating the accuracy of the marginal land classification by comparing it against established CRP land cover, which serves as a form of ground truth in my analysis. According to the analysis, the total CRP land cover that falls within the CLU boundaries is 1203603.5 Hectares.

Aggregating non-marginal lands

Following the same methodology, Common Land Units (CLUs) containing non - marginal land covers have been identified. For this analysis, we consider LCC class 1 to class 3, as non-marginal lands. According to USDA, LCC classes 1, 2, and 3 are most suitable for common crop production. Thus, these classes can be considered as non-marginal land cover with high productivity. Appendix B, supplementary section 2.4 outlines the methodology adopted to analyze non-marginal land cover in Kansas.

Aggregating non-CRP lands

A random selection process (randomly selected CLU polygons) was employed to identify non-CRP land cover within the CLU boundary. This random selection method was conducted on the CLU polygons that don’t contain any CRP land cover. Moreover, all wetlands, urban and forest covers are removed to assess the accuracy of marginal land covers (Following section 2.3.6.1: Step 02). The selection of non-CRP lands is directly proportional to the number of CLUs that comprise CRPs (Conservation Reserve Program) land cover. The selection process will be constant while assessing the accuracy of marginal lands in Kansas.

2.3.6.3 Accuracy Assessment and Validation

The process of assessing accuracy typically uses a reference dataset to determine the accuracy of a classified result. Here, the CRP or conservation reserve program land covers are considered as ground truth polygons to identify the accuracy of classified marginal land cover. After converting marginal, non-marginal, CRP and non-CRP land cover from a 30m resolution observation scale to a common land unit scale, I calculated the producer's accuracy, user's accuracy, and error rate of the classified marginal land cover. Here, the producer's accuracy is a metric used to calculate the accuracy of a map from a map maker's or producers' perspective. This assessment provided an estimation of the probability that a certain landcover on the ground (CRP) is classified as marginal land. On the other hand, the user's accuracy measures the probability of a class/land cover (marginal lands) being present on the ground (CRP lands) from a map user's point of view.

The error rate is a measure that tells us how many observations were classified incorrectly compared to the total number of observations. I calculated the error rate by summing the false positives (FP) and false negatives (FN) resulting from the spatial analysis of land classification (marginal, non-marginal, CRP, and non-CRP), then dividing by the total number of observations (true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN)).

All these accuracy measurement criteria have been calculated for the different marginal land threshold values (25%, 50% or 75%) under CLU scale. This analysis will provide an understanding of accurately classified marginal lands in Kansas.

2.4 Result and Discussion

2.4.1 Distribution of marginal lands in Kansas

To identify marginal land within Kansas, a multi-criteria analysis approach was employed in ArcGIS Pro interface. Each of the designated criteria either related to biophysical characteristics or land cover features was represented as raster layer with a spatial resolution of 30m. The geoprocessing to show the distribution of marginal lands in Kansas is conducted at 30m observation scale. Biophysical criteria include factors such as slope, drainage, flood risk, and erosion risk. Land cover features include criteria such as non-prime farmlands, conservation reserve program (CRP) enrollment, barren land cover, and land capability class (LCC). I have reclassified the raster datasets to convert them into binary rasters, with 1 indicating the presence of the criterion, and 0 representing its absence.

Biophysical Marginal Criteria: In ArcGIS Pro, various soil biophysical attributed are aggregated into a singular assessment of marginal land distribution. This methodology involved the utilization of reclassified binary raster layers corresponding to distinct soil parameters: drainage, erosion, slope, and flood frequency. Subsequently, a composite raster layer was created through a pixel-by-pixel summation using the Raster Calculator tool in ArcGIS Pro formulated as **“bio_sum = Raster(drainage) + Raster(erosion) + Raster(slope) + Raster(flood_frequency)”**. This process amalgamated the individual impacts of each criterion into a cumulative biophysical marginality index, by identifying areas with various degrees of marginality. The composite raster delineates the distribution of marginal lands by categorizing areas into five distinct classes, each representing the sum of conditions present: from class 0 indicating no marginality to class 4 maximum marginality (Figure 2.15).

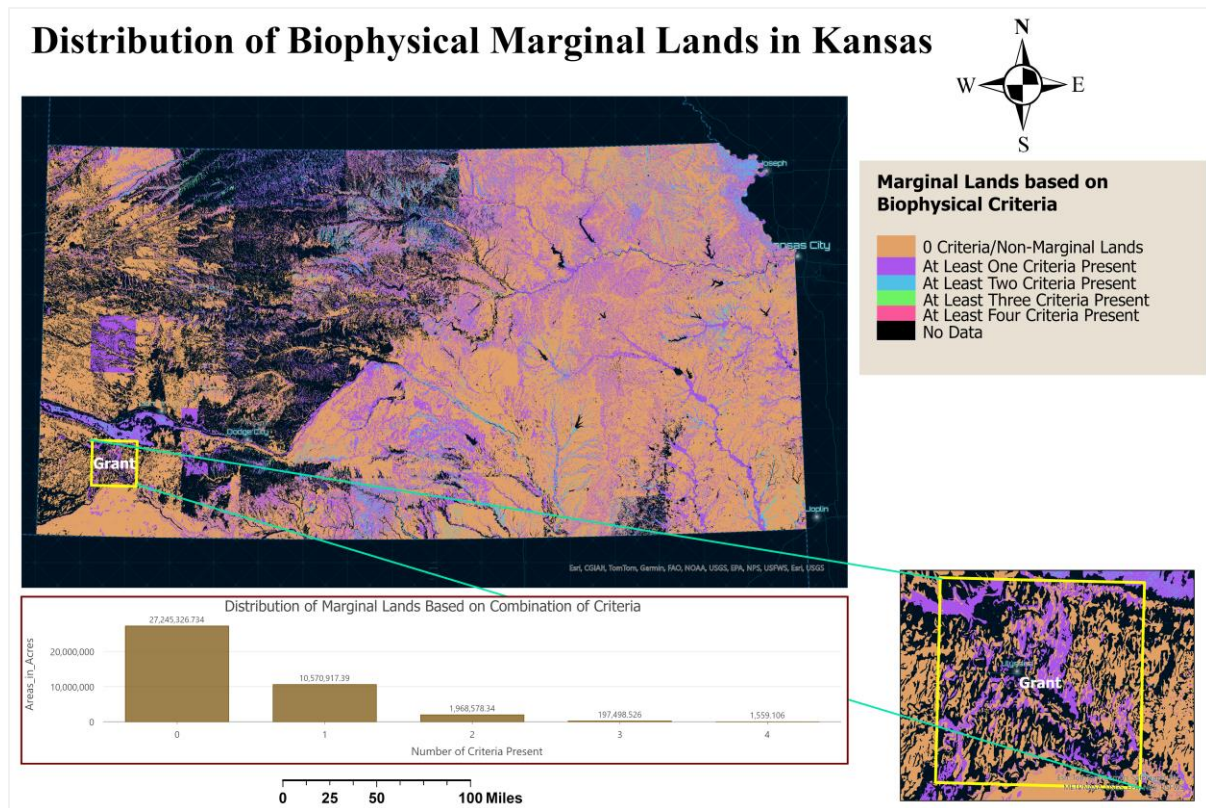


Figure 2.15: Distribution of Biophysical marginal lands in Kansas.

Table 2.4 outlines the distribution of marginal land cover across Kansas. Class 0 represents areas with no biophysical marginality, comprising over half of Kansas's total area. 1 indicates presence of at least one biophysical criterion, covering 10570917.39 acres of lands in Kansas. Progressively, Class 1 through Class 4 represent lands meeting 1 to 4 criteria, respectively, with Class 1 covering 20.08% of Kansas and progressively smaller percentages for higher classes, indicating land covers that meet two to all biophysical marginality criteria.

Table 2.4: Distribution of marginal lands based on soil biophysical criteria

Number of Combined Criteria	Area in Acres	Area in Acres (% of Kansas)	Area in Hectares	Area in Hectares (% of Kansas)
0	27245326.73	68.14%	11045402.73	68.14%
1	10570917.39	26.44%	4285507.05	26.44%
2	1968578.34	4.92%	798072.3	4.92%
3	197498.526	0.49%	80066.97	0.49%
4	1559.106	0.004%	632.07	0.004%

Land cover based Marginal Land: Criteria following the same methodology in ArcGIS Pro, a geographical analysis was conducted to synthesize distinct land cover categories: barren lands, CRP lands, land capability class, and non-prime farmlands. The final composite raster provides distribution of marginal land in Kansas based on the land cover criteria. Figure 2.16 shows the distribution of land cover-based marginal lands in Kansas.

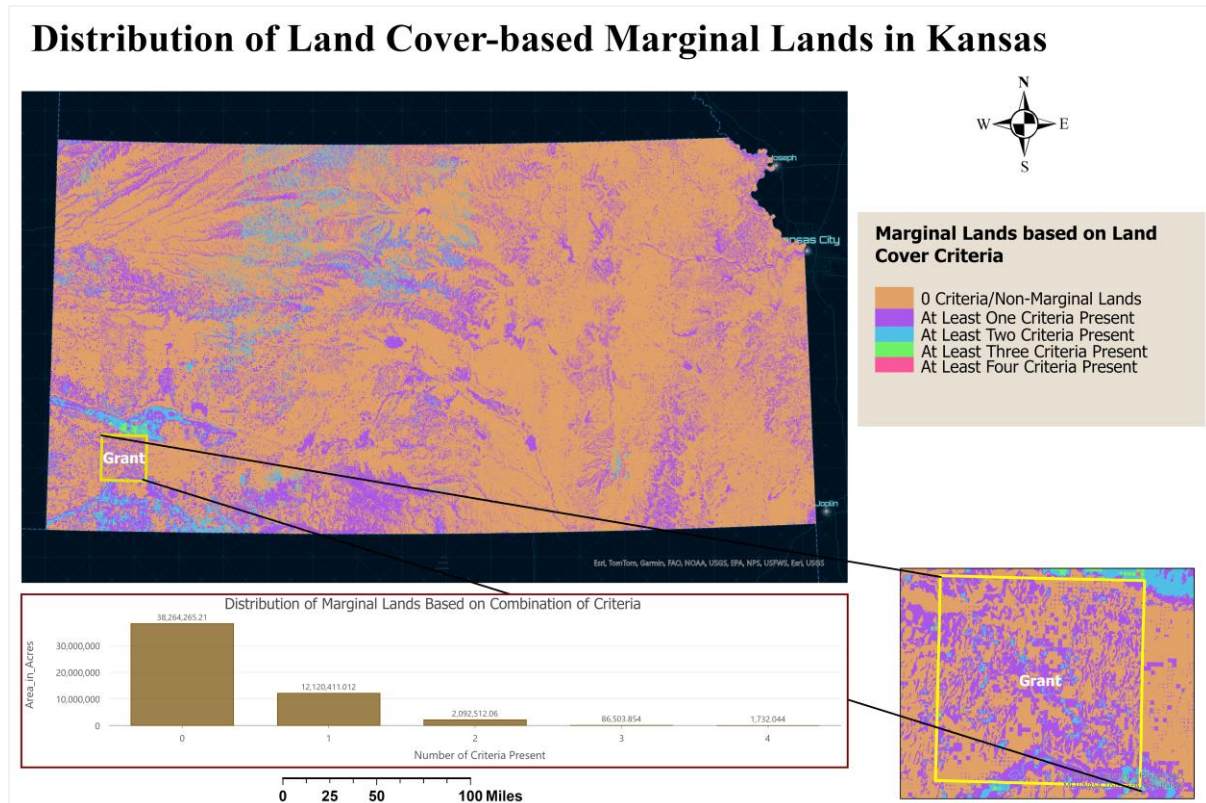


Figure 2.16: Distribution of land cover - based marginal lands in Kansas.

Table 2.5 summarizes output by categorizing Kansas’s landscape into distinct classes. Class 0 encompasses 38264265.21 acres of land in Kansas and represents 72.67% of the state, showing no marginality based on land cover criteria. While class 1 through 4 demonstrates increasing levels of marginality which is contingent upon the presence of 1 to 4 specific land cover criteria.

Table 2.5: Distribution of marginal lands based on land cover criteria

Number of Combined Criteria	Area in Acres	Area in Acres (% of Kansas)	Area in Hectares	Area in Hectares (% of Kansas)
0	38264265.21	72.67%	15512539.95	72.78%
1	12120411.01	23.03%	4913680.14	23.075%
2	2092512.06	3.97%	848315.7	3.98%
3	86503.854	0.16%	35069.13	0.16%
4	1732.044	0.0033%	702.18	0.0033%

A significant overlap is observed between biophysical and land cover based marginal land categories. Table 2.6 enlists the total area of marginal land by combining at least two criteria that overlap (areas/pixels where any two of these biophysical and land cover criteria overlaps). Here, bold characters represent criteria from different categories (either from biophysical or land cover) and normal font shows criteria that belong to similar categories. For instance, land covers that are poorly drained are also considered as non-prime farmlands and fall under land capability class 5-7. A majority of CRP land covers are eroded land parcels as per the result presented in Table 2.6. Both CRP land cover and land capability class 5 to 7 are highly flood prone areas. Thus, it is observed that both biophysical marginal lands and land-cover based marginal lands share common attributes.

Table 2.6: Assessments of marginal land in Kansas based on the conjunction of two specific criteria.

Combining at least two criteria	Estimated Area in Acres	Estimated Area in Million Hectares
Poorly drained soil + Eroded soil	20,480.83	0.008
Poorly drained soil + Barren	15,403.91	0.006
Poorly drained soil + CRP	59,4370.6	0.24
Poorly drained soil + Non-Prime Farmlands	771875.4	0.31
Poorly drained soil + Flood-prone areas	4,477,743	1.82
Poorly drained soil + Land Capability Class (5-7)	892,651.6	0.36
Poorly drained soil + Steep Slope	510,959.9	0.21
Eroded soil + Steep Slope	290,720.8	0.12
Eroded soil + Land Capability Class (5-7)	311,423.8	0.13
Eroded soil + Flood-prone areas	20,480.83	0.008
Eroded soil + Non-Prime Farmlands	441,810	0.179
Eroded soil + CRP	102,247.7	0.04
Eroded soil + Barren	3,600.396	0.0015
Barren and CRP	40,432.42	0.016
Barren and Non-Prime Farmlands	29,355.06	0.01
Barren and Land capability classes (5-7)	8,565.204	0.0034
CRP and Non-Prime Farmlands	330,528.5	0.13
CRP and Land Capability Classes (5-7)	225,570.4	0.09
Steep Slope + Land Capability Class (5-7)	955,424.1	0.39
Steep Slope + Flood-prone areas	871,011.5	0.35
Steep Slope + Non-Prime Farmlands	344,0181	1.39
Steep Slope + CRP	134,837.5	0.05
Steep Slope + Barren	9,364.848	0.0037
Land Capability Classes (5-7) + Non-Prime Farmlands	1,724,046	0.70
Flood-prone areas + Non-Prime Farmlands	1,599,708	0.65
Flood-prone areas + Land Capability Class (5-7)	472,897.7	0.19
Flood-prone areas + CRP	394,858.5	0.16
Flood-prone areas + Barren	14,968.13	0.006

2.4.2 Combining Biophysical and Land cover criteria in delineating and validating marginal lands cover in Kansas

Section 2.3.2 provides a comprehensive understanding on the distribution of marginal lands in Kansas, predominantly focusing on selected criteria under two broad categories: (a) Biophysical and (b) Land cover. This section focuses on employing the framework discussed in section 2.3.2 by combining both biophysical and landcover criteria in a single land cover layer. Moreover, another significant addition to this section is validating marginal land cover data layer by utilizing Conservation Reserve Program data in the analysis. The geospatial analysis to delineate and validate marginal land cover follows a multi-step GIS workflow, culminating in a comprehensive dataset that provides detailed spatial information on marginal land distribution.

2.4.2.1 Overlay analysis combining all biophysical and landcover criteria

Overlay analysis produces varying amount of marginal land depending on the threshold applied (number of criteria applied). The more criteria a piece of land must meet, the more narrowly and stringently marginal land is defined, resulting in smaller areas being classified as such. For instance, when the most stringent condition is applied, requiring land to meet all the criteria (both biophysical and landcover) no marginal land pixel was found that fulfils the condition. While applying a less stringent condition of at least five criteria, approximately 9,346 acres or 0.0038 million hectares marginal land cover have been identified. Conversely, broadening the criteria (i.e., reducing the number of conditions that must be met) expands the scope of what is considered marginal, encompassing a larger area, and potentially including a wider variety of land types. Relaxing the conditions to require at least three criteria broadens the scope, with approximately 1,566,909 acres or 0.634 million hectares being identified as marginal, reflecting a more inclusive interpretation of marginality. The least stringent approach, considering land marginal if it meets any one of the specified criteria, yields the largest

classification, encompassing approximately 18,295,480 acres or 7.404 million hectares. Table 2.7 presents the criteria or thresholds adopted and the corresponding areas of marginal land within the State of Kansas. The resultant maps based on the conditions have been portrayed in Figure 2.17, 2.18, and 2.19 respectively representing the presence of at least one, three, and five criteria to define marginal lands in Kansas.

Table 2.7: Conditional assessment of marginal land criteria in Kansas.

Conditions	Marginal Land in MHa (Acres)
At least 5 criteria	0.0038 million hectares (9,346)
At least 3 criteria	0.634 million hectares (1,566,909)
At least 1 criterion	7.404 million hectares (18,295,480)

Distribution of Marginal Lands in Kansas

Presence of at least one criteria

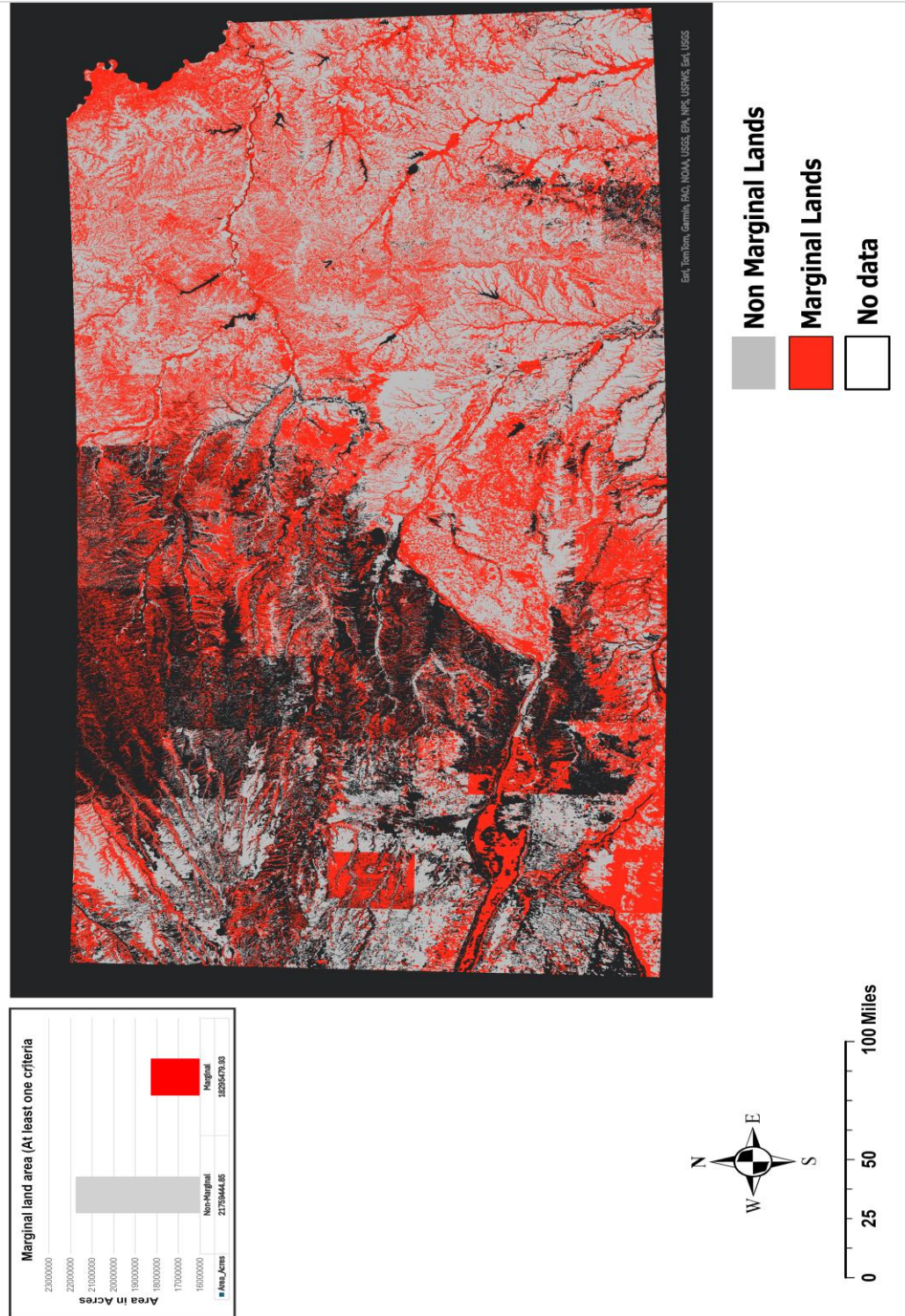


Figure 2.17: Distribution of marginal land based on combined (both biophysical and landcover criteria: at least one criteria)

Distribution of Marginal Lands in Kansas

Presence of at least three criteria

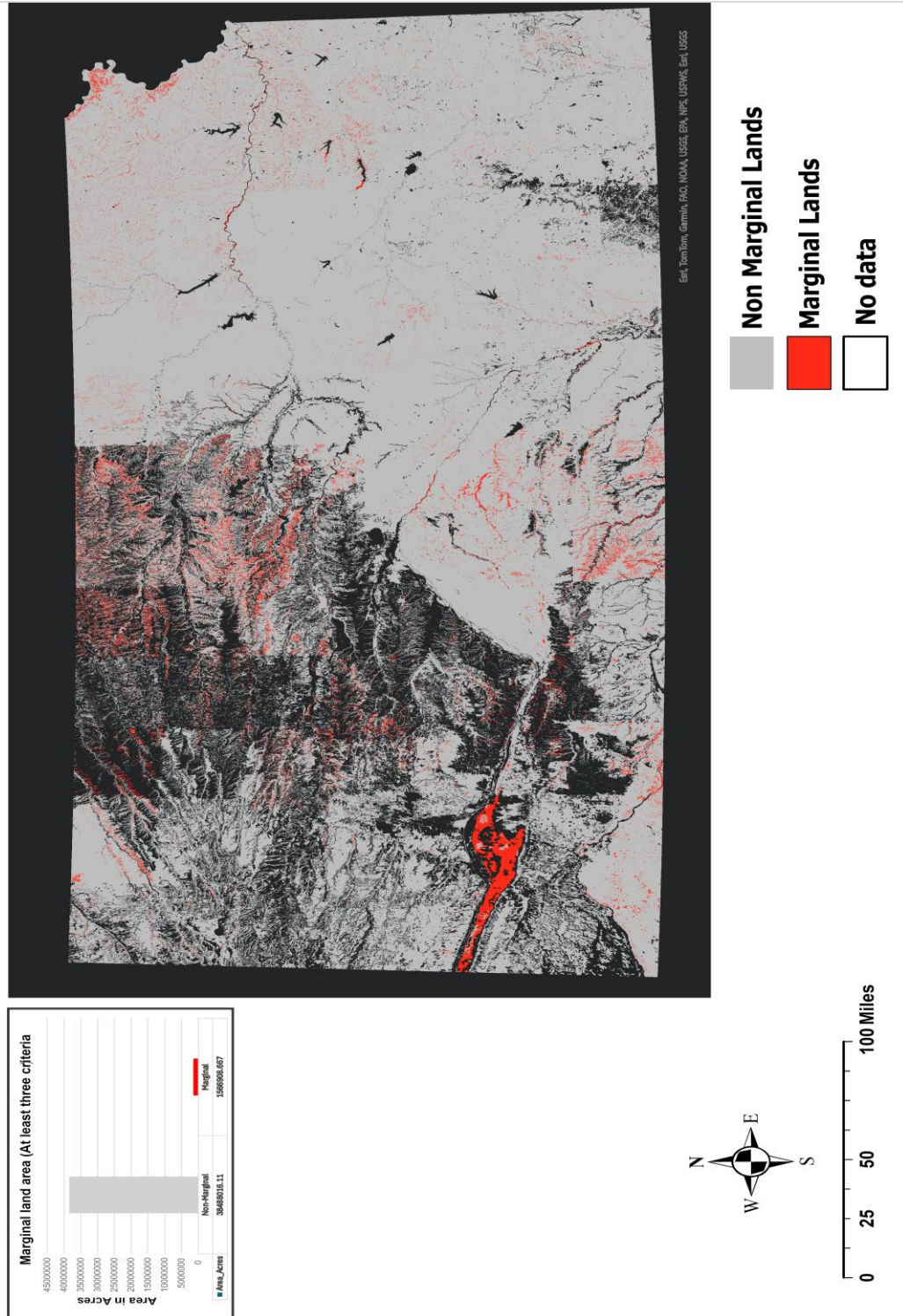


Figure 2.18: Distribution of marginal land based on combined (both biophysical and landcover criteria: at least three criteria)

Distribution of Marginal Lands in Kansas

Presence of at least five criteria

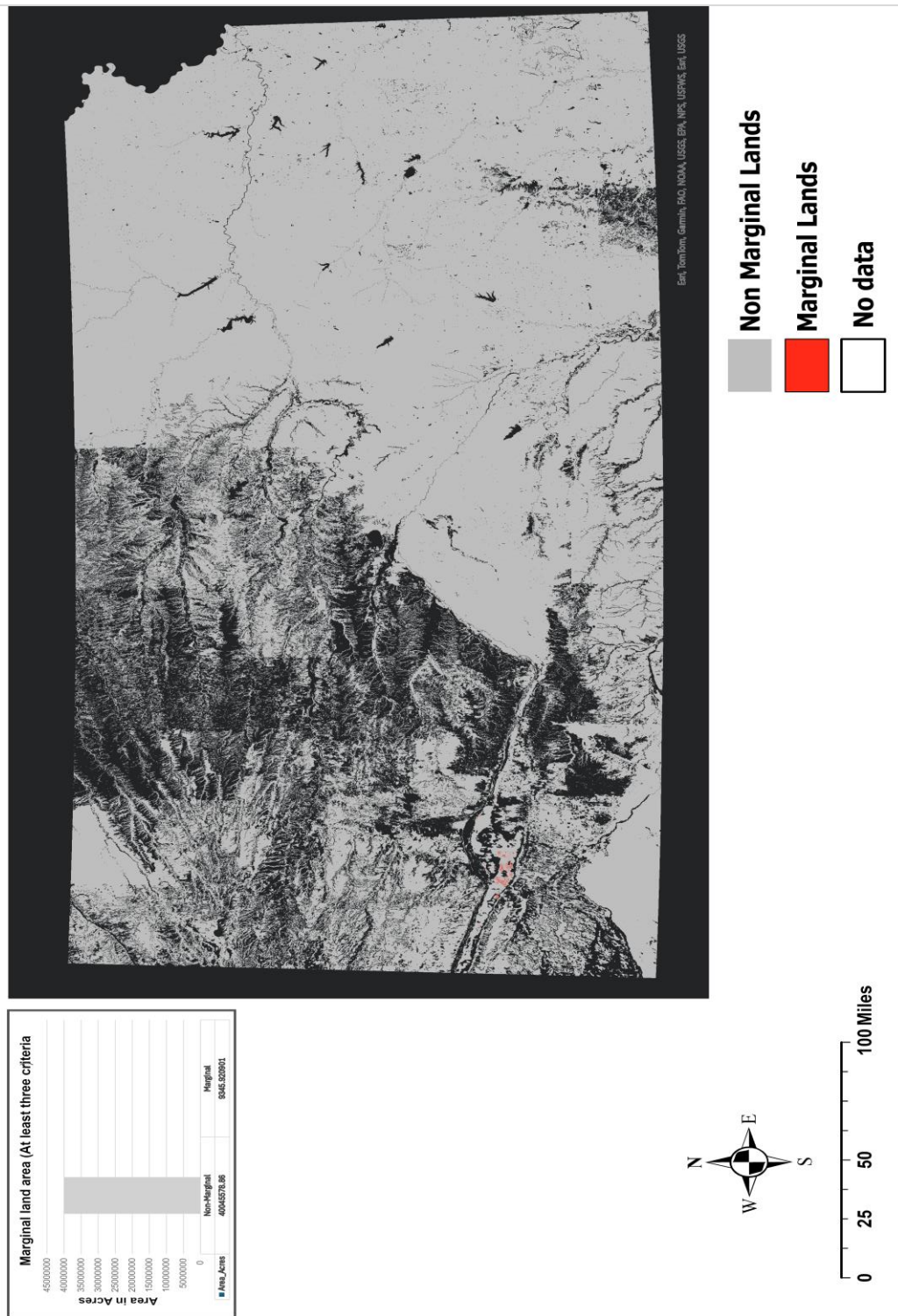


Figure 2.19: Distribution of marginal land based on combined (both biophysical and landcover criteria: at least five criteria).

2.4.2.2 Validation and accuracy assessment

2.4.2.2.1 Overlay analysis of marginal land cover criteria (Excluding CRP land cover)

In the first step of accuracy assessment, I estimated the marginal land cover excluding CRP land under consideration. To achieve this, I followed the methodology outlined in section 2.3.6.1 (Step 01). Upon conducting conditional analysis, I found that 0.00002304 million hectares (MHa) of land cover met at least five criteria (any of the seven criteria) to classify as marginal lands. By lowering the requirement to at least three criteria, I identified roughly 0.574 MHa of marginal lands. Lastly, with the least stringent approach of at least one criterion, I identified around 6.915 MHa of marginal lands. Table 2.8 lists the criteria and associated distribution of marginal lands in Kansas. For the purposes of further analysis, I will be utilizing the least stringent approach, classifying a land cover as marginal land if it meets at least one criterion.

Table 2.8: Criteria and Corresponding Marginal Land Areas in Kansas

Conditions	Marginal Land (MHa)
At least 5 criteria	0.000124 million hectares
At least 3 criteria	0.574 million hectares
At least 1 criterion	6.915 million hectares

2.4.2.2.2 CRP lands accurately classified as marginal lands

To test my hypothesis that CRP lands are primarily marginal I have calculated the area of CRP lands that are correctly classified as marginal lands by performing a spatial analysis in ArcGIS Pro. The total area of CRP land was approximately 12,036,034,987 square meters (1.20 million hectares). This area represents the intersection of CRP lands and CLU boundaries.

Following the 25% threshold, I found approximately 39.35% of CRP lands were accurately classified as marginal land based on the intersection of CRP and marginal land dataset. This result confirms that to a certain extent the CRP lands possess the characteristics of marginal lands. This result also provides an estimation of total marginal land cover area that is accurately assessed. The total area of marginal lands that overlap with CRP land cover is approximately 473558.02 hectares. As the threshold criteria moves from 25% to 75%, a decrease in total area of CRP lands classified as marginal is observed. Table 2.9 demonstrates a comparative analysis of the impact of threshold rules on the classification of CRP land as marginal. At the 50% threshold, a smaller area (279097.18 hectares or 689,664.16 acres) of CRP land is classified as marginal, accounting for 23.19% of the total CRP land. Lastly, the 75% threshold results in only 151,875.89 hectares or 375,308.61 acres which portrays only 12.62% of CRP lands being classified as marginal.

Table 2.9: Classification of CRP Lands as Marginal by Threshold

Threshold	Total Area of CRP Lands (Hectares)	Area Classified as Marginal (Hectares)	Percentage Correctly Classified
25%	1203603.5	473558.02	39.35 %
50%	1203603.5	279097.18	23.19 %
75%	1203603.5	151,875.89	12.62 %

Producer's and User's Accuracy, and Error rate

To further evaluate the reliability of the marginal land classification methodology based on specific threshold, I have also calculated both Producer's and User's Accuracies. Here, producer accuracy helps understand how well the marginal lands are captured by the geospatial analysis, whereas the user's accuracy reflects the likelihood of CRP lands truly representing the marginal land cover on the ground. Depending on the threshold selected I compiled varied

producer's and user's accuracy in Table 2.10. From the table, a significant difference is observed in the producer's accuracy and user's accuracy across the three different threshold levels (25%, 50%, and 75%). A higher producer's accuracy was observed at the 25% threshold compared to the accuracy of higher threshold values. No clear trend was observed for user's accuracy. However, under the stricter criterion, the 75% threshold provides a slightly better accuracy compared to other thresholds. The error rates remain considerably identical across all thresholds. However, a slightly decreasing trend is observed with increasing threshold which reflects fewer classification errors.

Table 2.10: Accuracy assessment criteria

Threshold	Producer's Accuracy	User's Accuracy	Error rate
25%	29.30	24.05	46.61 %
50%	21.50%	23.39%	44.37 %
75%	15.48	24.93	40.70 %

The major goal of my thesis is to maximize the identification of all potential marginal land. To achieve this goal, I have considered several factors such as producer's accuracy, user's accuracy, error rate and most significantly the total area of CRP lands classified as marginal land cover. After this comprehensive analysis, I have concluded that the 25% threshold is the most suitable for further analysis on identifying suitable solar photovoltaic sites in Kansas. This threshold not only provides an optimal balance between identification of marginal lands but also avoids any possible misclassification. Figure 2.20 shows an overall distribution of marginal land cover in Kansas based on the 25% threshold value. Based on my assessment, the 25% threshold provides 473558.02 hectares or 0.47 million hectares of marginal lands in Kansas. The validation of marginal lands shows that CRPs are not completely marginal. A major proportion of CRP lands are non-marginal.

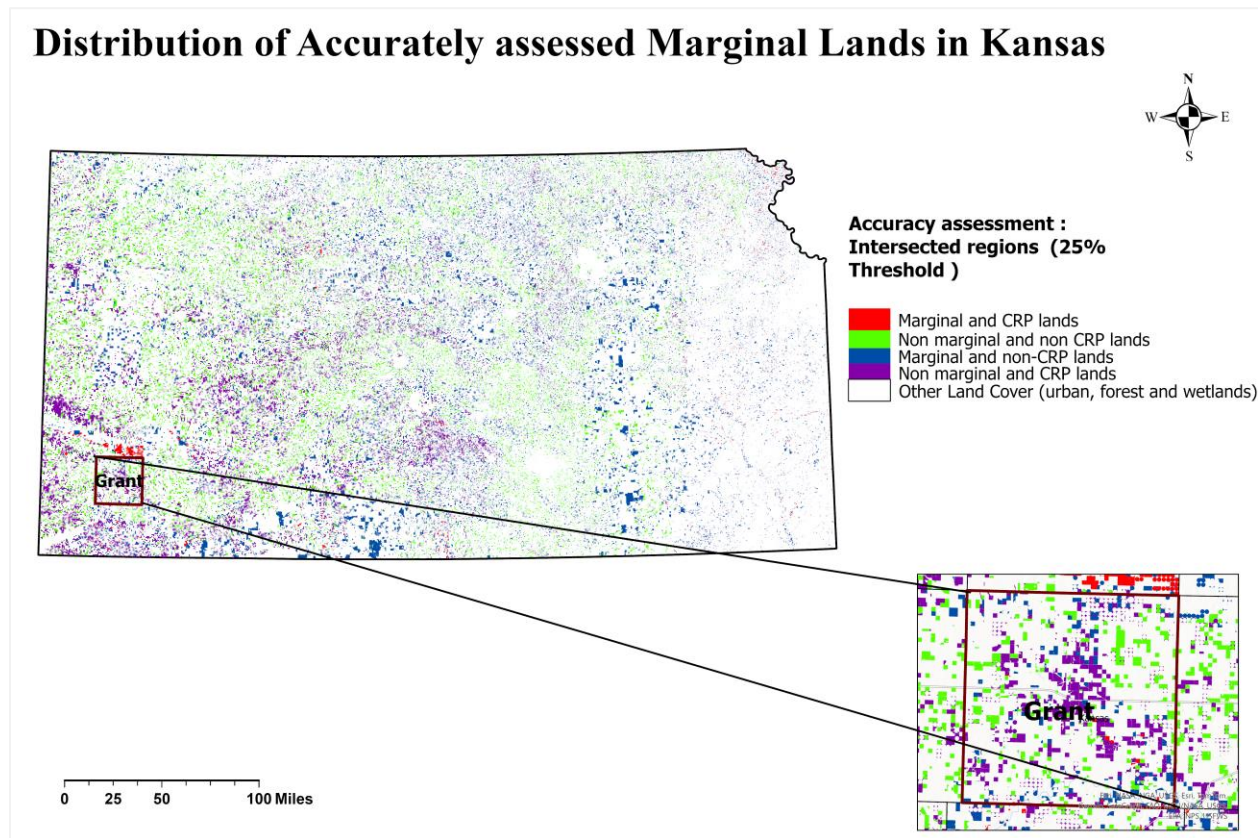


Figure 2.20: Accurately assessed marginal lands in Kansas

2.5 Limitation and Future works

The process of identifying, delineating and accurately assessing marginal lands has certain caveats. One of the major limitations of this research is the reliance on remotely sensed datasets. Almost all criteria except for the Conservation Reserve Program land cover have been acquired as raster datasets. These raster data have their own quantified error rate. I have adopted these data sources, as these secondary remotely sensed data are the only obtainable data source and previous researchers have adopted these data to conduct similar research. Moreover, datasets

related to soil properties are considered constant, while they are subjected to change due to several factors (environmental, economic or social). Modification of these soil properties could potentially alter the delineated marginal land cover, which is associated to certain degrees of uncertainty. Furthermore, the framework adopted to identify marginal lands in Kansas is strictly contingent upon criteria that have been widely utilized by previous researchers. Thus, this research doesn't comprehensively include all the criteria used in previous research on identifying marginal lands. Lastly, this research is restricted to identifying and delineating contemporary marginal lands. Future studies could also investigate projected land cover change and subsequent change in marginal land cover in Kansas. Despite having certain limitations, this research can serve as a base to quantify and to validate marginal land cover for the entire US afterwards.

2.6 Discussion on marginal lands in Kansas

Energy security is a fundamental goal for national economies, ensuring the ability to meet current and future energy needs affordably, while prioritizing environmental sustainability and energy efficiency (Wyman and Dale, 2015; Winzer, 2012). However, the increasing energy consumption demand in the USA (EIA, 2023) has potential to exacerbate the existing competition for available land resources between agri-based food production and energy generation in rural USA (Calvert and Mabee, 2015; Khanna et al., 2021; Valentine et al., 2012).

Development of renewable energy sources on marginal lands provides an opportunity to meet the increasing demand of energy in the US. While there are certain limitations (environmental, locational or climatic) in utilizing marginal lands to deploy these energy projects, they still have the potential to ameliorate the increasing competition between agricultural lands and energy production.

Among numerous renewable energy sources, solar energy has gained tremendous acceptance for energy production in the US due to its clean, infinite, and noiseless nature (Eldin et al., 2015). Notwithstanding, solar microgrid or small-scale solar photovoltaic requires different amounts of land cover depending on the type of technologies employed. Researchers at the National Renewable Laboratory (NREL) have developed two metrics to assess the land area required for solar PV deployment. The first metric is the total land area, which encompasses PV deployment area as well as additional protected or fenced areas enclosed by the site boundary (Ong et al., 2013). The second metric is the areas that are directly affected by the PV deployment which is occupied by solar arrays, substations, and other related infrastructures. The National Renewable Energy laboratory has measured the land use requirement based on both capacity (area/MWac) and generation (area/GWh/yr6). According to their analysis, a small-scale solar photovoltaic system with a 1MW capacity requires a capacity-weighted average of 5.9 acres/MWac and 8.3 acres/MWac, respectively, for direct and total land use requirements (Ong et al., 2013).

According to my analysis, I have identified that there is a significant amount of marginal lands available in Kansas that has potential to be utilized for solar photovoltaic site selection. My research indicates that approximately 473558.02 hectares or 1170185.54 acres of marginal land can be considered for this purpose. These renewable energy prospects of marginal lands not only ensure a steady and reliable energy supply for Kansas and neighboring states but also safeguard the state's productive agricultural land cover.

2.7 References

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Chapter 3: Suitable SPV Site Selection in Kansas

3.1 Introduction

While solar energy travels to Earth as electromagnetic waves, composed of photons (Foster et al., 2010), the magnitude of solar energy or solar irradiance is not uniform rather its contingent upon spatio-temporal and meteorological components across different scales (local, regional, or global) (Redweik, et al., 2012). Thus, determining an optimal solar energy project, we require accurate estimation of incoming solar radiation, climatic (temperature, sunshine hour, humidity, and so forth), and other locational (proximity to transportation/transmission, restricted ecological region, and so forth), and economic (demand) parameters. Thus, the process of suitable site selection is very sophisticated as it is contingent upon selecting appropriate criteria that are favorable for solar photovoltaics. Additionally, owing to the inconsistency in climate, orography, geographical location, and other socio-economic factors, the selection of criteria also varies depending on the study area.

Numerous scholarly works have already been published on identifying suitable locations to install solar photovoltaics to generate electricity. However, no study has been conducted in Kansas. Furthermore, while selecting criteria, researchers have focused on climatic, social, and economic criteria; however, none of the previous research have focused on utilizing underutilized marginal land cover to install solar photovoltaic panels.

My research employs an algorithmic approach to identify optimum location for solar development on marginal lands in Kansas. I adopted a GIS-based multicriteria decision-making (MCDM) approach to evaluate the criteria involved in the site selection process. This analysis consists of three preponderant steps: (a) Identifying solar site selection criteria, (b) employing marginal land cover (Chapter 02) for solar photovoltaic site selection, and (c) utilizing an

Analytical Hierarchy process or AHP (an MCDM technique) to rank the selection criteria to leverage them in a GIS interface. The GIS-AHP method combines both qualitative and quantitative data and has been widely adopted by researchers in renewable and conventional energy planning, utility planning and resource allocation management (Garni and Awasthi, 2018; Pohekar and Ramachandran, 2004). Moreover, the use of multicriteria decision-making models facilitates the identification of optimal site locations that maximize the benefits and minimize the risks associated with solar development.

3.2 Background

3.2.1 An overview on photovoltaic (PV) technology

Photovoltaic (PV) technology is a renewable energy source that converts sunlight into electrical energy. PV cells are the basic building blocks of this technology and have the potential to produce up to 2 watts of power individually. When multiple PV cells are connected in chains, they form modules or panels that can be used independently or grouped together to create an array. Working in tandem, these arrays generate the necessary electric power to complete a PV system (U.S. Department of Energy) (Figure 3.1). This system is a sustainable and cost-effective way to generate electricity while reducing carbon emissions.

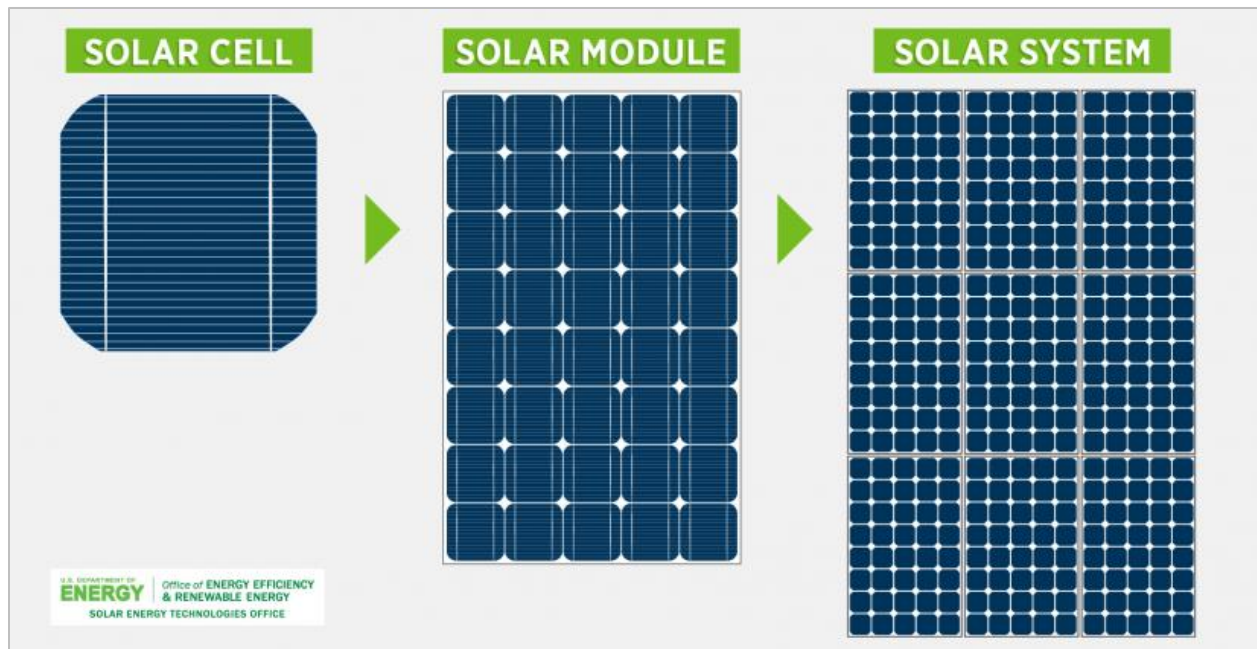


Figure 3.1: Building blocks of solar system (U.S. Department of Energy).

Photovoltaic cells are made of semiconductor materials which have the potential to convert light into electricity. The conductivity of a semi-conductor is more than a metal but less than that of an insulator. The photovoltaic conversion efficiency at a large-scale is contingent upon the ability of a solar cell to convert sunlight into electricity. Some other external factors that may modify the efficiency of a solar array are solar radiation incident, shading, heat, and dirt, dust, or leaves. (Gharehpetian et al.,2017; U.S. Department of Energy). Extreme environmental conditions, including snow, tornado or heavy rainfall might have a significant impact on photovoltaic conversion efficiency.

3.2.2 Utility scale and micro grid solar projects: Advantages, disadvantages, myths, and facts

Large-scale photovoltaic projects, known as utility scale utility-scale solar PVs, are connected to the central power grid and directly sell their generated electricity to local utility or other buyers. While the term ‘utility-scale’ is determined by size, different organizations follow/

assign distinct thresholds when defining utility-scale PV projects. For instance, according to Solar Energy Industries Association (2024), if a solar project has a capacity of 1 million watts or 1 megawatt (MW), it can be considered as utility scale. On the other hand, the National Renewable Energy Laboratory raises the threshold value to at least 5 MW for a solar project to be deemed as utility scale. Utility-scale solar projects typically range from 100-200MW, which optimizes the cost-benefit ratio of solar energy (Feldman et al., 2021). Utility-scale solar power has become deeply entrenched in terms of electricity generation capacity in the USA. According to the latest report in 2020, solar power contributes to 38% of all U.S. energy capacity additions, with utility scale accounting for 27%.

Despite being a relatively recent addition to U.S.s energy infrastructure, solar microgrids are gaining popularity due to their improved energy efficiency and reduced reliance on a centralized power system. Microgrids are small scale projects that generate and distribute electricity with or without any reliance on a central grid system. While both utility-sale and micro-grid have widely contributed to the state of electricity generation in the U.S., they have their own set of advantages and disadvantages which include land requirement, technical issues, or environment pollution. In Table 3.1 we will provide a list of prospects and limitations of utility-scale solar projects and microgrid solar projects.

Table 3.1: Comparative analysis of Utility-scale and microgrid solar projects

Utility-scale Solar Project		Microgrid Solar Project	
Advantage	Limitation	Advantage	Limitation
Utility scale projects do not produce greenhouse gasses, for instance CO ₂ or Volatile organic compounds (VOCs) (Environment America, 2008)	PV cells contain hazardous materials for semiconductor surface cleaning, posing a risk of silicon dust inhalation.	Microgrids can efficiently reduce carbon emission by deploying more electricity sources (Center for Climate and Energy Solutions. (n.d.).	The initial cost of developing and deploying microgrids can be high. However, governmental subsidies usually help ameliorate this burden (Shahzad, et al., 2023).

Utility-scale solar can supply energy during peak demand (middle of the day). With the rising population and its associated demand, utility-scale solar can be considered the most cost-efficient option (Sierra Club n.d.).	Utility-scale solar project requires vast amount of land, considering each MW of solar capacity demand 4-5 acres of land cover (NextEra Energy Resources).	Unlike utility-scale solar systems, microgrids are a form of distributed generation. This approach ensures that energy is not lost over long distances during transmission. Instead, it is generated close to the communities or sources where it will be utilized (Center for Climate and Energy Solutions. (n.d.).	Microgrids are designed for a small area or group of people, which limits their reliability for a larger community.
Utility solar panels are renewable; thus, they can be sited for at least 30-40 years or more (Sierra Club, n.d.).	Integrating large number of solar panels in areas with limited infrastructure (transmission grid) present challenges (Solar Energy Industries Association, n.d.)	Microgrids reduce reliance on centralized power systems. In the event of failures due to extreme weather conditions or cyber-attacks, microgrids can function independently, offering continuous electricity supply. This capability to operate in isolation is also referred to as islanding (Cummins Inc., 2021).	Microgrids require extensive regulatory and monitoring operation. Moreover, as they stepped in the energy market recently, there is a lack of legislation and regulation regarding microgrid operation (Shahzad, et al., 2023).
Utility-scale solar project creates local employment opportunities.	Local and state governments have varying regulations for utility-scale solar on agricultural land, which can complicate the sitting and development of these projects. Furthermore, often these projects face opposition from local communities or government that lack the expertise in site selection plans (Kleinman Center for Energy Policy).	The distributed nature of microgrids makes them more resistant to cyberattacks. If one power source is compromised, the system can rely on other sources, thus enhancing the overall security of the energy supply (Microgrid Knowledge, n.d.)	Solar microgrids are complicated to deploy and manage. Lack of experience in maneuvering a significant number of micro sources can pose potential technical challenges (Flynn,2022).

While utility-scale/microgrids are well recognized and widely adopted, numerous researchers (Tawalbeh et al.,2021; Mustafa et al., 2020; Tsoutsos et al., 2005; Rabaia et al., 2021; Qi and Zhang, 2017) consider SPV project detrimental to soil health, wildlife, public health, and so forth. For instance, according to solar projects can have a significant impact on

soil and prime farmland (Tsoutsos et al., 2005). Moreover, some researchers found that solar panels leach chemicals into the ground which are detrimental to health (Fthenakis, 2000). On the other hand, Tawalbeh et al (2021), Marwede et al. (2013), and Üçtuğ and Azapagic (2018) assert that PV panels contain and emit harmful material that can be detrimental to the environment, humans, and wildlife. While these research are based on empirical evidence, there also exist published government reports, magazines, documents that invalidate these outcomes. Table 3.2 enlists a few myths that people believe and the reality/facts about solar PV projects.

Table 3.2: Is solar panel detrimental to human, environment, and wildlife? The myths and realities

Myths	Facts/Reality
Solar projects have a detrimental impact on soil and prime farmlands in the future.	Farmlands under solar panels will not be utilized for any crop production, letting the soil rest during this period. These inactive periods of crop production will also restore soil fertility. Moreover, researchers have found that native vegetation cover under the arrays of solar panels support pollinator population (e.g. Bees). Studies have also shown that utilizing “Agtivoltaics” can benefit both crop production and energy generation (Harrison Dreves, 2019).
Solar panel leaches hazardous materials that can potentially pollute soil and ground water and pose a threat to public health.	Modern photovoltaic cells are made of solid materials and in most cases, they are sealed, thus unable to deteriorate soil or groundwater (Wiser et al., 2016).
SPV projects have a detrimental impact on the environment by polluting air and water pollution as well as driving away wildlife.	SPV projects are kept away from protected areas, for instance natural parks or wildlife sanctuaries. Moreover, they produce little noise with no emission of air or water pollutants (JPMorgan Chase and Company, 2020).
Solar panels are not safely disposed after use.	Modern solar panels are safely disposed of and recycled. Solar panel end life management also follow 3R approach (Reduce, reuse, and recycle) for an efficient waste management (Weckend et al., 2016).

Most of these myths and controversies are preponderantly based on the utility scale solar project. While microgrids are not devoid of limitations, they are indeed less pronounced and less controversial than utility scale solar projects. Moreover, researchers have identified microgrids

as sustainable infrastructure towards minimizing environmental pollution, and economic, environmental, and social cost.

3.2.3 Review of previous work on solar PV site selection

The task of determining criteria plays a crucial role in the implementation of a solar photovoltaic (SPV) facility. This decision-making process for choosing the site is of utmost importance, as the feasibility and success or failure of the project are entirely dependent on it (Sward et al., 2021). Numerous scholars have devoted their attention to identifying several factors that effectively determine the most suitable location for SPV development. However, the selection of these criteria varies based on the project objectives, data accessibility, and existing scholarly works (Al Garni and Awasthi, 2018).

Appendix C, supplementary section 01 provides a comprehensive collection of research undertaken from 2000 to 2022, encompassing the factors and techniques related to solar siting. These criteria vary considerably with geographical location, climatic factors, and data availability. Some factors might be considered as significant for a study area, which is less significant or negligible for others. However, some commonly used criteria for optimal solar site are solar insolation, slope, distance to road, proximity to residential areas, exclusion of protected areas (Sward et al., 2021; Kim et al., 2021; Colak et al., 2020).

Criteria can be divided into positive/selection criteria and negative indicators/constraints. Selection criteria are those factors which enhance the suitability of a site, on the contrary negative indicators are those which restrict the site suitability. For instance, selection criteria are slope within the range of 1% to 10%, south/southeast/southwest orientation, adjacent to road or electric infrastructure, and high solar irradiance, (Solangi et al., 2019; Koc et al., 2019; Jung et al., 2019; Shorabeh et al., 2019; Nay, 2018; Doljak and Stanojević, 2017). Restriction criteria

include protected areas, coastal zones, livestock trails, residential areas and historically important areas (Colak et al., 2020; Solangi et al., 2019; Watson and Hudson, 2015). While majority of research have prioritized geographic and locational factors (Solangi et al., 2019; Koc et al., 2019; Jung et al., 2019; Shorabeh et al., 2019; Nay, 2018; Doljak and Stanojević, 2017), few of the researchers have also included social (Solangi et al., 2019) and ecological (Colak et al., 2020; Solangi et al., 2019; Watson and Hudson, 2015; Calvert and Mabee, 2015) factors in the siting studies.

In previous research, scholars have utilized GIS-based multicriteria analysis to determine the optimal locations for SPV installations (Jung et al., 2019; Solangi et al., 2019; Sánchez-Lozano, et al., 2013; Uyan, 2013; Carrión et al., 2008). However, a noteworthy research gap exists regarding the inclusion of employing marginal land for the implementation of micro-grid SPV facilities, as no previous work has specifically addressed this aspect. Hence, there is a need for further scholarly exploration to assess the feasibility and potential benefits of utilizing marginal land for micro-grid SPV deployment.

The primary objective in addressing my research question is twofold, (1) to establish the key criteria that play a vital role in determining the appropriate location for implementing SPV projects and (2) to utilize marginal land cover for the SPV suitability analysis for Kansas. These criteria will be derived from a comprehensive analysis of existing literature pertaining to the selection of SPV sites. The marginal land cover data has been derived by utilizing specific sets of criteria that characterize marginal land. The framework adopted in identifying marginal lands, the method, and the resulting marginal land cover layer have been comprehensively discussed in chapter 02.

3.2.4 MCDA methods, application, and comparative analysis

3.2.4.1 Defining MCDA

Decision making processes in Geography, or any interdisciplinary science often gets complicated as it necessitates a blend of insights from biological/ecological science, earth science, human science or societal studies, governance or political studies, and moral philosophy for ethical considerations. Contemporary geographers rely mostly on spatial (mathematical, statistical or machine learning) and non-spatial (GIS-based, Agent based modelling, simulation models, spatial statistics, landscape ecology models or hydrology models) computational models to solve problems associated to urban and regional planning (Arampatzis et al., 2004), transportation (Okabe and Okunuki, 2001), energy (Alam et al., 2016), environmental management (Jim and Chen, 2008), epidemiology (Shi and Wang, 2015), climate change and meteorology (Sweeney et al., 2018; McKenney and Rosenberg, 1993), policy governance (Lettieri, 2016), agricultural and food security (Jin et al., 2020) and so on. However, these methods and tools have their own sets of caveats (Chen et al., 2020; Burke et al., 2020; Sirmacek and Vinuesa, 2022). Huang et al. (2011) identified three major limitations of these computational methods. Firstly, decisions related to climate change or nanotechnology have a considerable amount of uncertainty associated with them. Secondly, an abundance of evidence for a familiar problem sometimes provides conflicting results owing to its multiple sources of information. Furthermore, stakeholders, from community members to industry leaders, often share access to decision-making data but interpret it through their own interests and biases. The uncertain nature of this data can lead to conflicting viewpoints on the best course of action, exacerbated by stakeholders' increased access to information (Huang et al., 2011).

Multicriteria decision analysis (MCDA) provides a systematic framework that minimizes these uncertainties by assimilating stakeholder perspectives and rank the alternatives to get a refined output. MCDA has a common framework that includes the following key elements: **(a) Option:** course of actions required to move forward with a problem and an outcome; **(b) Objectives:** Selective goals associated for each option ; **(c) Criteria:** Indicators that ensure the fulfillment of an objective; **(d) Performance score:** A scale for each option based on their performance; and **(e) Criterion weight:** Assignment of a weight to each of the criterion based on the level of importance of an objective (Dean, 2020).

3.2.4.2 Extensively used MCDA Methods in Solar panel site selection

Implementation of multi-criteria analysis has been widely welcomed in different research domains. Researchers have provided numerous MCDA classification schemes based on rules, procedures, and mathematical principles. For instance, application of MCDA has been used for energy policy (Vasić, 2018), park selection (Zucca et al., 2008), urban transport investment (Tudela et al., 2006), forest management (Wolfslehner et al., 2005), environmental management (Khalili and Duecker, 2013) and so forth. Some widely used MCDA approaches are AHP (Analytical Hierarchy Processes), ANP (Analytical Network Process), TOPSIS (Technique for Order Preference by Similarity), ELECTRE (Elimination and Choice Expressing Reality), WLC (Weighted Linear Combination), and so forth. However, some of the most widely used MCDA approaches in solar site selection are AHP, FAHP, ANP, OWA, Fuzzy OWA, ELECTRE, TOPSIS, VIKOR and so forth (Afzali et al., 2014). Table 3.3 shows MCDA methods that have been employed by different scholars. AHP and WLC are the two most extensively used MCDA

methods for solar site selection. A description of some of the most widely used MCDA methods is provided below in Table 3.3.

Table 3.3: MCDA methods used in previous research on solar site selection.

MCDA Methods	Energy sector	References
AHP	Solar	Colak et al., 2020; Alhammad et al., 2022; Koc et al., 2019; Watson and Hudson, 2015; Yunna and Geng, 2014; Yun-na et al., 2013; Uyan, 2013; Effat, 2013; Carrión et al., 2008; Rumbayan and Nagasaka, 2012
ANP	Solar	Uyan and Dogmus, 2023; Aragonés-Beltrán, et al., 2010; Lee et al., 2017.
AHP-fuzzy VIKOR approach	Solar	Solangi et al., 2019).
Ordered Weighted Averaging (OWA)	Solar	Shorabeh et al., 2019
Fuzzy OWA		Aydin et al., 2013
WLC	Solar	Anwarzai and Nagasaka, 2017; Castillo et al., 2016; Brewer et al., 2015; Janke, 2010
Interpretive Structural Modeling (ISM), Analytic Network Process (ANP), VIKOR (Vlsekriterijumska Optimizacija I Kompromisno Resenje)	Solar	Lee et al., 2017.
AHP-Fuzzy TOPSIS	Solar	Sindhu, et al., 2017.
AHP—TOPSIS	Solar	Sánchez-Lozano et al., 2013
AHP-Fuzzy-WLC	Solar	Zoghi et al., 2017
FAHP	Solar	Noorollahi et al., 2016.
FAHP-DEA	Solar	Lee et al., 2015
ANN	Solar	Borgogno Mondino et al., 2015
ELECTRE-II	Solar	Jun et al., 2014; Sánchez-Lozano et al., 2014
DEMATEL—DANP	Solar	Chen et al., 2014

1. AHP:

AHP or Analytical hierarchy process was proposed by Saaty (Saaty et al., 2013; Zare et al., 2016). AHP is a widely applied decision-making model that decomposes a problem in

different levels in a top-down hierarchical approach. Here the topmost level explains the ultimate goal of the decision problem and the middle levels are the criteria and sub criteria that help to reach the goal. Lastly, the bottom tier is the alternatives that are evaluated according to established criteria. A scale of 1-9 (based on Saaty's scale) is assigned to each level of the hierarchy based on the relative importance of the objective/criteria in solving the specific problem. Nevertheless, a weighted assessment is also employed by AHP by assigning weight to the criteria based on their relative importance (Aragonés-Beltrán et al., 2010).

2. ANP:

A special type of AHP, ANP or Analytic Network Process has also been proposed by (Saaty et al., 2013). ANP doesn't follow a hierarchical model, rather it solves a problem as a network where nodes are the cluster of criteria/elements and the arcs portray the relationship between the nodes (Uyan and Dogmus, 2023). ANP can be a useful tool where the criteria have an intricate relationship. ANP prioritizes all alternatives that support decision making (Quezada et al., 2021) and follows a hierarchical approach; however, it does not do this using a top-down way that AHP proceeds with.

3. WLC

Weighted Linear Combination or WLC is another widely used MCDA model, where it standardizes all criteria in a numeric range and then combines them by employing a weighted average. WLC can be easily executed in a GIS interface (e.g. ArcGIS Pro, QGIS or IDRISI) by employing an overlay analysis. Performing a WLC requires the following steps: determination

of criteria, standardizing of criteria, determining weights of criteria, generating weighted maps, and generating final overlaid maps.

4. ELECTRE

The Elimination and Choice Expressing Reality or ELECTRE method was first proposed by Roy and Vanderpooten in 1996 (Roy and Vanderpooten, 1996). The distinctiveness of this method lies in the consideration of both qualitative and quantitative criteria (Figueira et al., 2016). ELECTRE methods are constructed using a set of binary outranking relations S . Here, “ S ” refers to “at least as good as”. This outranking relation is contingent upon two major concepts (a) Concordance, where the validation of an outranking aSb is contingent upon the consensus of the majority of criteria; and (b) non-discordance, where no criteria can oppose assertion that aSb , when the concordance condition is met (Figueira et al., 2016).

5. TOPSIS

TOPSIS or Technique for Order Preference by Similarity to an Ideal Solution is a well-recognized classical decision-making technique that carries out analysis by comparing and ranking alternatives. TOPSIS was developed by Hwang and Yoon in 1981 (Yoon, 1981) based on the notion that the most suitable alternative will have the shortest distance from the positive ideal solution (A^*) and the farthest distance from the negative ideal solution (A^-). For example, a positive ideal solution will maximize functionality and minimize the cost of product, whereas a negative ideal solution will minimize functionality and maximize the cost of product. The major steps in TOPSIS include (a) evaluation of alternatives based on a normalized decision matrix, (b) determining positive and negative ideal solution, and (c) determining final ranks. TOPSIS has

been adopted widely. For instance, it has been used in manufacturing processes (Shukla et al., 2017), stock exchange assessment (Hatami-Marbini and Kangi, 2017; Bulgurcu, 2012), software selection (Hanine et al., 2016), waste management model (Mir et al., 2016), and so forth. While considering adoption of TOPSIS in SPV site selection, we found plenty of researcher who deem TOPSIS as an effective method (Sindhu et al. 2017; Akçay and Mehmet, 2018; Badi et al., 2023; Nazari et al., 2020; Kengpol et al., 2013; Sánchez-Lozano et al., 2016).

Each of these abovementioned MCDA methods has their advantages and limitations. In Table 3.4, a concise list of merits and demerits of certain MCDA techniques is provided.

Table 3.4: Merits and demerits of MCDA methods

MCDA Techniques	Advantages	Limitations
AHP	▪ Universality ▪ Reduced subjectivity ▪ Verification of data inconsistency ▪ Systematic consideration of tangible and intangible factors (Kou et al., 2016) ▪ Considers subjective objective or qualitative/quantitative information. ▪ Model elasticity can be analyzed by sensitivity analysis. ▪ Widely utilized in planning, risk analysis, site selection and other decision-making processes.	▪ Highly computational ▪ Based on probability and possibility measure ▪ Linear increase of time and effort with increasing levels of hierarchy (consistency matrix). ▪ Takes both probability and possibility measures into consideration.

ANP	▪ Simplify complex problems. ▪ Prioritize indicators/cluster of elements () ▪ Can handle input and output with multiple units.	▪ Reliance on expert opinion ▪ Can result in unwieldy model. ▪ Greater complexity than AHP
WLC	▪ Reduce complexity in analysis. ▪ Handles both qualitative and quantitative criteria. ▪ Flexible and efficient in suitability evaluation,	▪ High reliance on expert opinion. ▪ Oversimplifies complex problems.
TOPSIS	▪ Simplicity and practicality ▪ Effectively combines different criteria. ▪ Useful for group decision environments.	▪ Sensitivity to normalization ▪ Unable to handle human subjectivity.
ELECTRE	▪ A simple well refined computational process. ▪ Utilizes outranking process. ▪ Imperfect knowledge is processed by indifference and preference thresholds. ▪ Non-compensatory in nature.	▪ Threshold values have a significant impact on final result. ▪ Time consuming. ▪ Uncertainty in accuracy exist in ELECTRE I ▪ Unable to handle ordinal scale.
OWA	▪ Combines both Boolean Overlay operation and	▪ Dependence on weight assessment can be subjective which

	weighted linear combinations. Provides flexibility in Aggregation by adopting Boolean operation (“or” to “and”).	consequently derives biased and inconsistent results.
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3.3 Materials and methods

The selection of suitable SPV sites is contingent upon several environmental, social, economic, and climatic factors (Garni and Awasthi, 2018). I adopted a GIS-based MCDA (Multicriteria Decision Analysis) approach to assess the suitability of marginal lands for solar micro-grid installations. This assessment will include selection, climatic (solar irradiation, temperature, sunshine hour), locational (distance from roads and transmission lines), and orographic (slope and aspect) criteria, as well as several restriction criteria for instance, protected areas, forest, cropland, wetland, urban area and so forth. I will utilize AHP (Analytical Hierarchy Process), a widely adopted MCDA technique to solve complex problems by choosing the best alternative from a set of criteria. The AHP method is extensively contingent upon expert opinion. Thus, I initiated the process of identifying a panel of experts from solar photovoltaic sectors. These individuals are chosen based on their experience, academic credentials, and contribution to the field. The panel of experts in the field of SPVs includes professionals from energy agencies, electric power companies, and faculty experts from Kansas State University. The survey was designed to utilize the AHP's pairwise comparison technique, enabling participants to evaluate various criteria against each other on a ratio scale (1 to 9). This scale is fundamental to the AHP methodology, as it allows for a nuanced expression of preferences, quantifying how much more one criterion is preferred over another. Specifically, the scale ranged from 1 (equal importance)

to 9 (extreme importance), facilitating the precise measurement of the relative importance of climatic, locational, and orographic factors in the selection of solar microgrids. Based on these expert opinions and AHP the weights for each criterion under consideration are then estimated. Subsequently, these weights and associated criteria will be introduced in a GIS interface to evaluate multiple criteria spatially and hierarchically to identify optimal location for solar microgrids. This combined approach leverages the strengths of both AHP for decision making and GIS for spatial analysis, offering a comprehensive tool for site selection that considers both the qualitative judgments of experts and quantitative spatial data. The proposed method to accomplish this thesis has been illustrated in Figure 3.2. This framework includes following stages, (a) Identifying experts from academic and industrial background to conduct an expert opinion survey (b) defining major climatic, environmental, and technical constraints in deploying SPVs in Kansas, (c) determining specific selection criteria which help identify the most suitable location for SPV in marginal lands of Kansas, (d) eliminating restricted areas by overlaying all layers in a GIS interface (e) evaluating the weights of each selection criteria using AHP, and (f) preparing a SPV site suitability map for marginal lands in Kansas by overlaying site selection criteria and their associated weight in GIS.

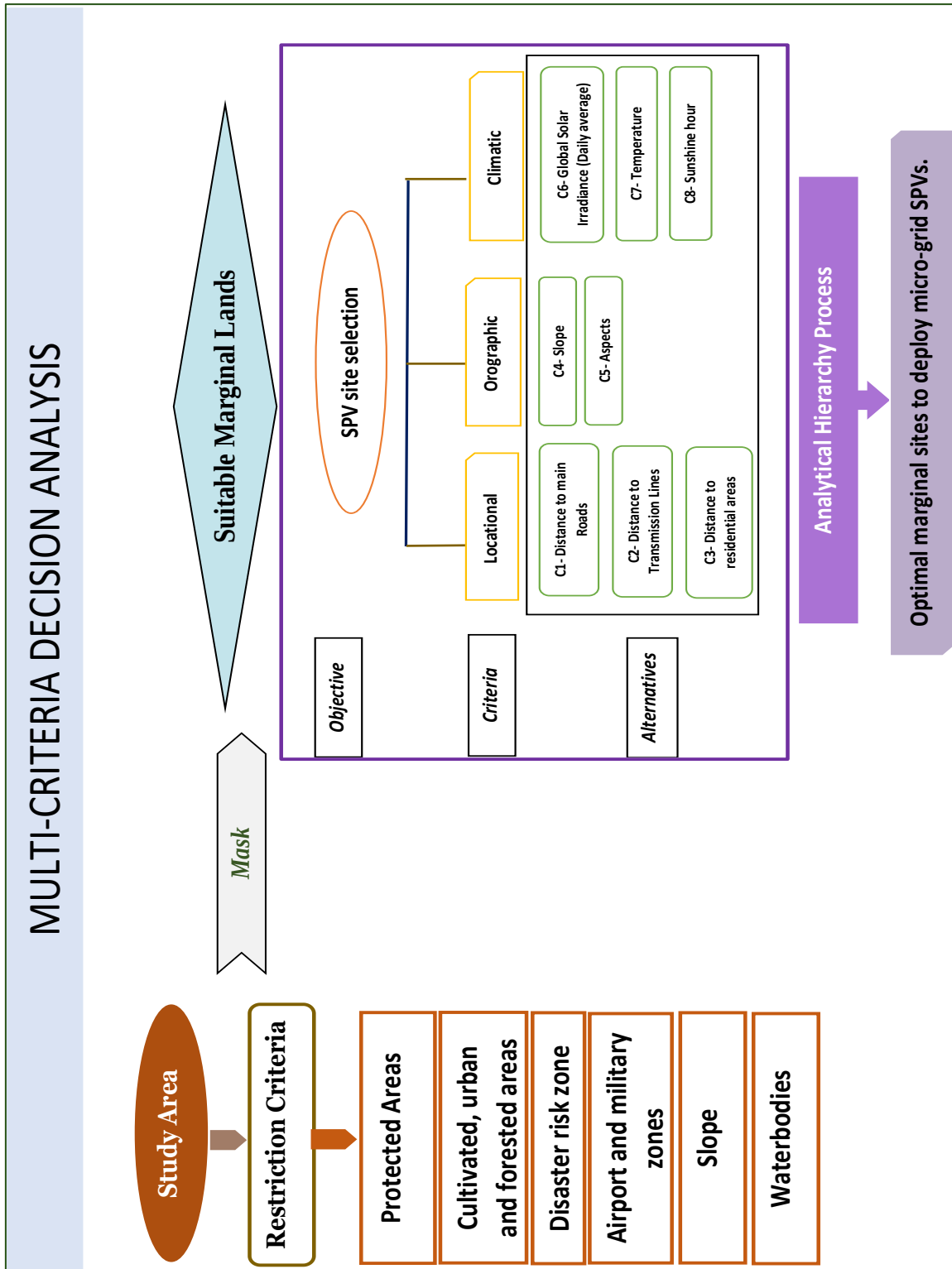


Figure 3.2: Adopted flowchart to conduct SPV site suitability analysis in Kansas

3.3.1 Study Area

For this section I will be utilizing the marginal land data layer derived from our first research question in Chapter 2. Figure 3.3 provides a map of available marginal lands that can potentially be utilized for solar PV site selection. According to research question 1, the State of Kansas has 0.474 million hectares (1,170,185.51 acres or 473,558.02 hectares) of marginal lands available. However, not all these marginal lands can be equally exploited for solar PV development. Furthermore, a large percentage of these marginal lands are explicitly unsuitable for any development projects and include protected areas, lands adjacent to waterbodies, urban areas, forest, and seasonal wetlands.

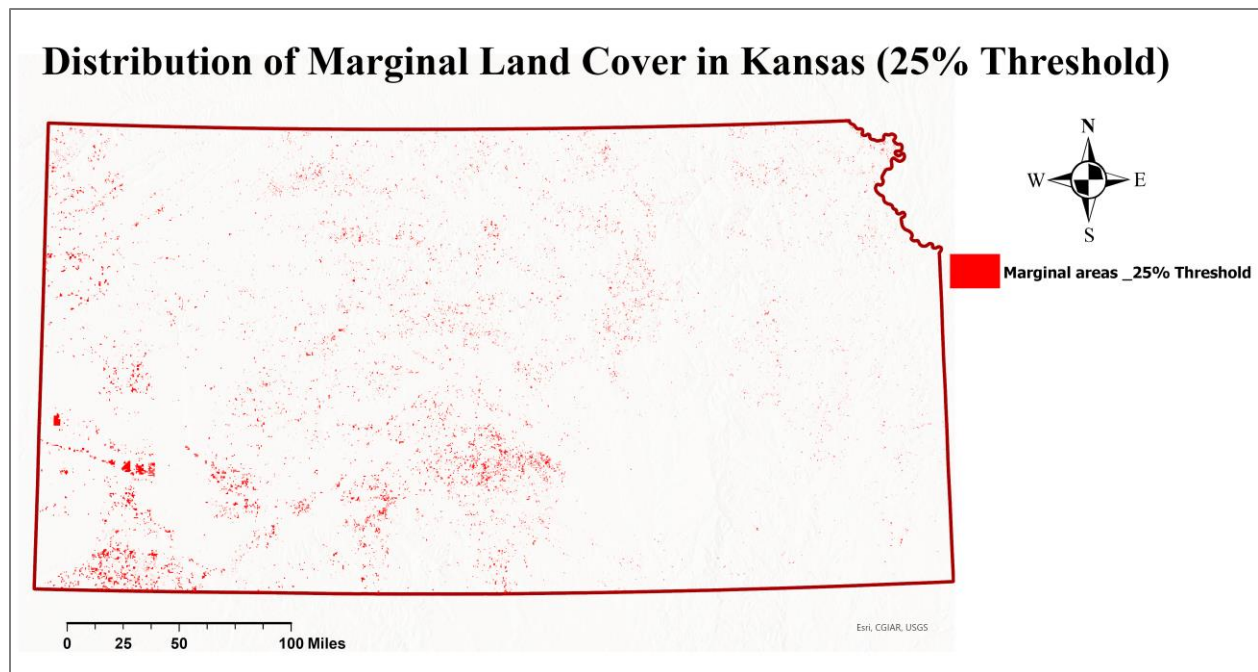


Figure 3.3: Available marginal lands within Kansas.

3.3.2 Data defining major criteria

Identifying potential/suitable sites for the development of micro-grid SPV is contingent upon considering the most significant and accurate criteria, which varies by geographical location (Sener et al., 2010; Kucuksari et al., 2014). Researchers have provided numerous factors or criteria to determine suitable location for solar panel development (Al Garni and Awasthi, 2018). The variation in criteria selection also depends on geo-referenced data accessibility of the correspondent study area. To identify the criteria in the context of our study area, we have undertaken an intensive literature review that allows us to consolidate the most crucial factors that have been widely applied by researchers for SPV site selection. Furthermore, to acquire a comprehensive understanding of the site selection criteria, we referenced the scholarly work by Garni and Awasthi (2018) that examined SPV factors in previously published papers. The major criteria/factors can be divided into two broad categories, ***Constraints/Restriction criteria*** and ***Suitability factors***.

3.3.2.1 Restriction criteria

According to Malczewski (1999), constraint factors are the limits or boundaries that are applied to a set of alternatives. They play a significant role in eliminating alternatives areas, based on a given attributes or feature values. Development of SPVs is also restricted in certain areas because of environmental or technical constraints. The constraints or exception criteria are utilized to exclude areas with higher priority purpose, areas protected by laws, or areas that are not suitable for the construction of SPV (Doljak and Stanojević, 2017; Castillo et al., 2016). Following Garni and Awasthi (2018), we found that, these restricted parcels are mostly protected

areas, transportation routes, natural disaster zones, waterbodies/wetlands, urban areas, residential areas, and wilderness areas. Table 3.5 shows the list of exclusion criteria and their data sources that we have considered for our constraint analysis.

Table 3.5: Major Restriction criteria, sub-criteria, and data sources

Major Restriction Criteria	Sub-criteria	Data sources	Data Type	References
Protected areas	Natural Park	USGS Protected Areas Database of the United States	Vector	Sun et al., 2021; Uyan et al., 2013
	Critical habitat	USFWS (U.S. Fish and Wildlife Service) Critical Habitat	Vector	
Disaster Risk zone	Flood Risk zone	Eastern Kansas Major Floodplains	Vector	Kengpol et al., 2012; Majumdar and Pasqualetti, 2019
Specific land use	Urban area	NLCD (National Land Cover Data)	Raster	Shorabeh et al., 2019; Sindhu et al., 2017; Zoghi, et al. 2017; Watson and Hudson, 2015; Uyan, 2013
	Forest cover	USDA Crop Data layer 2022	Raster	Shorabeh et al., 2019; Solangi et al., 2019
	Cultivation zone	USDA Crop Data layer 2022	Raster	Watson and Hudson, 2015; Majumdar and Pasqualetti, 2019; Yushchenko et al., 2018
Infrastructure	Airport	USGS National Transportation Dataset (NTD) for Kansas.	Vector	Kandt and Romero, 2014; Anwarzi and Nagasaka, 2017
	Military zones	USGS	Vector	Uyan 2013

	Roads	USGS National Transportation Dataset (NTD)	Vector	Abdulaziz et al., 2022; Uyan, 2013
Waterbodies	Wetlands	NLCD (National Land Cover Data)	Vector	Majumdar and Pasqualetti, 2019
	Probable Playas	Kansas Biological Survey	Vector	
Orography	Slope	United States Geological Survey (USGS)	Raster	Noorollahi et al., 2016; Baban and Parry, 2001

3.3.2.2 Selection criteria

Based on existing literature on SPV site selection, I have categorized the selection criteria under three broad categories, (a) Locational, (b) Orographic, and (c) climatic. The adoption of multicriteria decision analysis is an efficacious way to choose the best option/alternative based on multiple criteria. Table 3.6 provides a comprehensive list of all selection criteria and relevant data sources that are used for the purpose of selecting solar PV sites in Kansas.

(a) Locational Criteria

This major group includes criteria like distance to main roads, distance to transmission lines, and distance to residential areas. Proximity to residential areas ensure the accessibility to ensure the utilization of produced energy and access to required manpower. The National Land Cover Data has been utilized to extract urban land cover information and these data have been processed using GIS tools. The locational criteria would help choosing the best location which has the best accessibility to transportation network and transmission lines, which reduces the operational cost of SPV installation. Nonetheless, distance to urban areas ensures that SPV sites maintain adequate distance from residential areas. The data pertinent to roads and transmission lines were obtained from the USGS National Transmission Dataset and Homeland Infrastructure Foundation-Level data and GeoPlatform ArcGIS Online respectively.

(b) Orographic Criteria

Orographic criteria, such as slope and aspects, help with understanding terrain morphology (Bognar, 1990). In terms of engineering and geology, optimal locations for building SPV are typically found on terrains that are either level or have a minor southward slope (Tahri et al., 2015). We subdivided the orographic criteria into slope and aspect. Selecting the right slope is crucial as it not only facilitates easier access to the site but also simplifies the construction process, ensuring smooth transportation of materials. The southward slopes are mostly sunny throughout the year (Wolfe, 2012), which is another requirement to find the most suitable site for SPV installation. The USGS National Elevation Dataset (NED) was used to derive slope information of Kansas. The same dataset was utilized to calculate the aspects of the study area.

(c) Climatic criteria

Climatic criteria are considered as the most significant criteria when selecting the best location for SPV deployment. Global solar irradiation, duration of sunshine, and average annual temperature helps evaluate the feasibility and efficiency of SPVs. The data relevant to global horizontal irradiation, annual sunshine hour, and average annual temperature have been derived from Global Solar Atlas, NASA Power, and PRISM Climate Group respectively.

Table 3.6: Selection criteria data type, source, and supporting references.

Major Criteria	Sub-criteria	References	Source and Metadata	Data-format
Locational	Road	Alhammad et al. (2022); Colak et al. (2020); Solangi et al. (2019); Shorabeh et al. (2019); Sabo et al. (2019); Sindhu et al. (2017); Zoghi et al. (2017); Merrouni et al. (2016); Castillo et al. (2016); Tahri et al. (2015); Brewer et al. (2015);	Source: USGS National Transportation Dataset (NTD) Metadata: https://thor-f5.er.usgs.gov/ngtoc/metadata/waf/transportation/ntd/shapefile/TRAN_Kansas_State_Shape.xml	Vector/ Shapefile (.shp)

		Chen et al. (2014); Sánchez-Lozano et al. (2013); Effat (2013); Uyan (2013); Janke (2010);		
	Transmission Lines	Alhammad et al. (2022); Colak et al. (2020); Solangi et al. (2019); Koc et al. (2019); Sabo et al. (2019); Sindhu et al. (2017); Zoghi et al. (2017); Noorollahi et al. (2016); Castillo et al. (2016); Merrouni et al. (2016); Brewer et al. (2015); Chen et al. (2014); Sánchez-Lozano et al. (2013); Effat (2013); Uyan (2013); Janke (2010);	Source: <u>Homeland Infrastructure Foundation-Level Data (HIFLD) & GeoPlatform ArcGIS Online</u> Metadata: https://www.arcgis.com/sharing/rest/content/items/bd24d1a282c54428b024988d32578e59/info/metadata/metadata.xml?format=default&output=html	Vector/ Shapefile (.shp)
	Distance to residential areas	Alhammad et al. (2022); Colak et al. (2020); Solangi et al. (2019); Shorabeh et al. (2019); Sindhu et al. (2017); Zoghi et al. (2017); Merrouni et al. (2016); Castillo et al. (2016); Tahri et al. (2015); Chen et al. (2014); Sánchez-Lozano et al. (2013); Effat (2013); Uyan (2013); Janke (2010).	NLCD	
Orographic	Slope	Alhammad et al. (2022); Colak et al. (2020); Solangi et al. (2019); Koc et al. (2019); Shorabeh et al. (2019); Jung et al. (2019); Sabo et al. (2019); Guaita-Pradas, Inmaculada et al. (2019); Nay (2018); Zoghi et al. (2017); Noorollahi et al. (2016);	<u>USGS</u>	Raster (.tif)

		Castillo et al. (2016); Merrouni et al. (2016); Wang et al. (2016); Brewer et al. (2015); Tahri et al. (2015); Chen et al. (2014); Sánchez-Lozano et al. (2013); Effat (2013); Uyan (2013); Aydin et al. (2013); Janke (2010); Arnette and Zobel (2011).		
	Aspects	Colak et al. (2020); Solangi et al. (2019); Koc et al. (2019); Jung et al. (2019); Zoghi et al. (2017); Doljak and Stanojević (2017); Castillo et al. (2016); Watson and Hudson (2015); Tahri et al. (2015); Chen et al. (2014); Sánchez-Lozano et al. (2013); Effat (2013); Arnette and Zobel (2011).	<u>USGS</u>	Raster (.tif)
Environmental/Climatic	Global Solar Irradiance (Daily average) (kWh/m ² /day)	Alhammad et al. (2022); Colak et al. (2020); Solangi et al. (2019); Koc et al. (2019); Shorabeh et al. (2019); Jung et al. (2019); Sabo et al. (2019); Guaita-Pradas, Inmaculada et al. (2019); Zoghi et al. (2017); Doljak and Stanojević (2017); Noorollahi et al. (2016); Castillo et al. (2016); Merrouni et al. (2016); Wang et al. (2016); El - Azab and Amin (2015); Borgogno Mondino et al. (2015); Brewer et al. (2015); Tahri et al. (2015); Jun et al. (2014); Mahtta et al. (2014); Chen et al. (2014); Chakraborty et al. (2014); Yun-na et al. (2013); Sánchez-Lozano et al. (2013); Effat (2013); Besarati et al (2013); Rumbayan et al. (2013); Charabi, and	<u>Global Solar Atlas</u>	Raster (.tif)

		Gastli (2011). Aydin et al. (2013); Janke (2010).		
	Average annual temperature	Solangi et al. (2019); Koc et al. (2019); Guaita-Pradas, Inmaculada et al. (2019); Doljak and Stanojević (2017); Noorollahi et al. (2016); Borgogno Mondino et al. (2015); Chen et al. (2014); Sánchez-Lozano et al. (2013); Jain et al. (2011); Arnette and Zobel (2011).	<u>PRISM Climate Group</u>	Raster (.ascii)
	Sunshine duration	Shorabeh et al. (2019); Sabo et al. (2019); Zoghi et al. (2017); Doljak and Stanojević (2017); Castillo et al. (2016); Merrouni et al. (2016); Yun-na et al. (2013).	<u>NASA POWER</u>	.csv

3.3.3 Analytical Hierarchical Process (AHP) and GIS Processing

AHP is an analytical (and/or mathematical) technique widely adopted for organizing and analyzing complex decisions. It was developed by Thomas L. Saaty in the 1960s and since then has been extensively utilized in decision-making processes across various fields. This multicriteria decision model tool simplifies complex problems by breaking them down into a hierarchy of more easily comprehensible sub-problems, each of which can be analyzed independently (Sindhu et al., 2017; Talinli et al., 2011; Saaty, 2008). The Saaty's fundamental scale ranks alternatives on a scale of 1 to 9 which is provided in Table 3.7. The analytical hierarchy process has four major principles,

1. Problem detection and creating a hierarchy: identifying suitable solar photovoltaic locations based on locational, climatic, and orographic criteria;

2. Creating a comparative decision-making preference matrix;
3. Determining weight matrix for each criterion, which will be converted into normalized weight vectors which is contingent upon the level of importance of used criteria; and
4. A consistency ratio, calculated from the normalized weights, using the formula in equation 1, where CI represents a consistency index and RI represents random index.

$$\mathbf{CR\ (Consistency\ Ratio)=\ CI\ (Consistency\ Index)/\ RI\ (Random\ Index).....(1)}$$

Matrix consistency is essential in the AHP evaluation process, which involves ensuring that the matrix elements are linearly independent. The consistency index or CI helps determine the consistency of decision-making method. They help to determine the consistency of a decision-making method, with CI being the measure of consistency and RI being the measure of randomness. The consistency index evaluates the linear dependence of matrix elements. To assess CI, the first step is calculating the highest eigenvalue of the matrix (Equation 01).

$$\lambda_{max} = \sum_{j=1}^m \frac{(S.v)_j}{m.v_j}$$

Here, m signifies the number of independent rows within the matrix, S denotes the pairwise comparison matrix, and v represents the matrix eigenvector. The consistency index hence can be computed as follows:

$$\mathbf{CI = \frac{(\lambda_{max}-m)}{m-1}.....(2)}$$

According to the existing research on AHP, if the CR is less than 0.1 it will be considered as standard, and the binary comparisons are acceptable. And if the value is greater than 0.1 that means the binary comparison contradicts each other.

Table 3.7 : Saaty's fundamental scale

Scale	Definition	Explanation
1	Equal importance	Two criteria contribute equally to the objective.
3	Moderate importance of one over another	Expert opinion/judgement slightly supports one criterion over another
5	Essential of strong importance	Experts strongly consider one criterion more important than another.
7	Very strong importance	Experts very strongly consider one criterion more important than another
9	Extreme importance	Experts consider one criterion extremely more important than another
2,4,6,8	Intermediate values	When compromise is needed

3.3.3.1 Consistency ratio calculation

The end goal of Saaty's AHP is to determine weights for each sub-criteria associated to the site selection process. These weights will further be implemented in a GIS interface to identify suitable location for SPV projects by analyzing factors that have direct impact on them. I have conducted an expert opinion survey that includes subjective opinion from diverse fields to design the pairwise comparison on the linear scale of 1-9. An overview of the experts that are interviewed during this research has been listed in Table 3.8. Information regarding organization and expert's name have been kept confidential, however, an individual ID has been assigned to each respondent to calculate the consistency matrix and associated weights.

Table 3.8: Description of expert's current role and expertise

Id	Current Role	Area of Expertise	Year of Expertise
Expert #1	General Manager of Joint Action Agency	Power Industry in general	≥ 15
Expert #2	Manager, Power Contracts	Resource Adequacy/Resource Planning	10-14
Expert #3	Professor	Electric Power Systems	≥ 15
Expert #4	President	BSEE, PE Solar Development, Design, Engineering	≥ 15
Expert #5	Development	Development	6-9
Expert #6	Chief Operating Officer	Power Supply and Generation	≥ 15
Expert #7	Research & Development	Power Systems	6-9

Based on selected eight criteria, an 8*8 matrix was developed. The normalized weight vectors were calculated based on allocated importance (level of importance chosen by experts) of each criterion. After that, the matrix consistency has been determined based on the pairwise comparison. A random index of 1.41 was identified, which has further been used to calculate the CR (Consistency ratio). The value random consistency index is reliant on the matrix size. Table 3.9 provides an estimation of different RI (derived from Saaty, 2016) values that are contingent upon the matrix size. Finally, the CR has been calculated.

Table 3.9: Matrix size and associated RI values

Matrix Size	1	2	3	4	5	6	7	8	9	10
RI	0.00	0.00	0.58	0.58	1.12	1.12	1.32	1.41	1.45	1.49

Source: (Saaty, 2016)

According to Saaty (2016), the consistency ratio value of the pairwise matrix must be less or equal to 0.10 to be considered as acceptable in AHP. Table 3.10 provides a pairwise comparison of eight criteria to depict the relative importance of selected criteria.

Table 3.10: Pairwise comparison matrix of SPV site selection criteria

Criteria	Solar Irradiance	Sunshine Hour	Distance from Transmission Lines	Proximity to Transportation Routes	Distance from Residential Areas	Temperature	Slope	Aspects
Solar Irradiance	1	5	1/5	7	1/5	9	1	1
Sunshine Hour	1/5	1	1/9	1/5	1/9	5	1/5	1
Distance from Transmission Lines	5		1	9	1	9	5	5
Proximity to Transportation Routes	1/7	1/5	1/9	1	1/9	1	1/7	1/3
Distance from Residential Areas	5	9	1	9	1	9	9	9
Temperature	1/9	1/5	1/9	1	1/9	1	1/5	1/5
Slope	1	5	1/5	7	1/9	5	1	7
Aspects	1	1	1/5	3	1/9	5	1/7	1

3.3.3.2 Reclassification and weighted Overlay analysis

Each criterion has been reclassified into an identical scale, starting from 1 to 5, where 1 represents most suitable and 5 represents least suitable. Afterwards these classified criteria have been utilized to perform a weighted overlay analysis in ArcGIS Pro. Weighted overlay analysis is a widely adopted method in MCDA-based decision-making approach. For each reclassified criteria a weight has been assigned (calculated using AHP processing), where each cell's suitability value has been multiplied by the raster layer weight. Afterwards a weighted overlay has been applied to estimate an output with a common scale based on different raster layers. The common scale in ArcGIS Pro interface was used to identify the most to least suitable location for SPV development.

3.3.4 Constraints criteria analysis

This section provides a comprehensive analysis of criteria for restricting solar photovoltaic development, along with associated resulting maps. Table 3.11 summarizes the threshold values/amounts to consider certain land cover as restricted for solar photovoltaic development, based on previous literature. Figure 3.4 provides the framework adopted to process the restriction criteria in ArcGIS Pro interface.

Table 3.11 : Restriction criteria threshold and supporting literature.

Sub-criteria	Distance Threshold	Reference
Protected Areas	500m	Sun et al., 2021; Uyan et al., 2013
Flood Risk zone	No Buffer	Kengpol et al., 2012; Majumdar and Pasqualetti, 2019
Urban area/Residential areas	500m	Shorabeh et al., 2019; Sindhu et al., 2017; Zoghi, et al. 2017; Watson and Hudson, 2015; Uyan, 2013
Forest cover	No buffer	Shorabeh et al., 2019; Solangi et al., 2019
Cultivation zone	No buffer	Watson and Hudson, 2015; Majumdar and Pasqualetti, 2019; Yushchenko et al., 2018
Airport	100m	Kandt and Romero, 2014; Nagasaka 2017.
Military zones	500m	Uyan, 2013
Wetlands	200m	Majumdar and Pasqualetti, 2019
Probable Playas	No buffer	
Slope	>10%	Noorollahi et al., 2016; Baban and Parry, 2001.

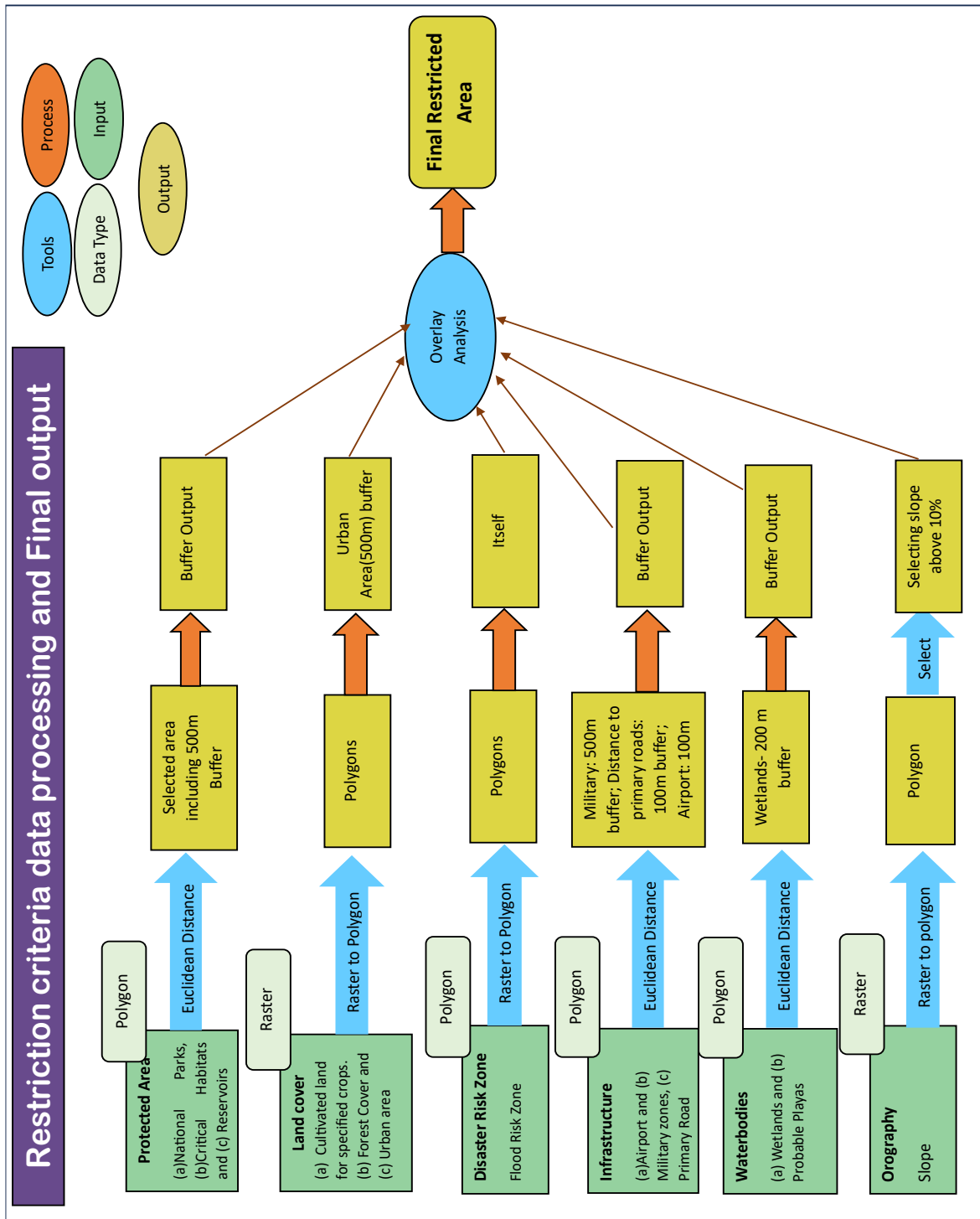


Figure 3.4: Processing constraints criteria for SPV site selection.

1. Protected Areas

According to IUCN (International Union for Conservation of Nature), a protected area “is a clearly defined geographical space, recognized, dedicated and managed, through legal or other effective means, to achieve the long-term conservation of nature with associated ecosystem services and cultural values”. Protected areas include wildlife sanctuaries, parks, natural reserves, biodiversity hotspots, critical habitats, and wetlands (Sward et al., 2021). Developing SPVs on these sites might adversely affect wildlife and their habitat. In my research, all natural parks, protected lakes and reservoirs and critical habitats inside Kansas were included under the “protected area” theme. When former researchers have only focused on excluding protected areas (Carrión et al., 2008; Kengpol et al., 2012; Merrouni et al., 2014), recent scholars have extended the boundary of excluded area by eliminating a specific buffer distance to ensure the least potential disturbance created by solar panel installation. However, the range of recommended buffer distance varies with a range of 500m (Sun et al., 2021; Uyan, 2013) to 1000m (Watson and Hudson, 2015; Al Garni and Awasthi, 2017). Following previous literature, a buffer distance of 500m buffer around protected areas was restricted for PV deployment (Uyan, 2013; Sun et al., 2021). For data sources, I attempt to incorporate data from different sources. The data related to National Park and critical habitats was collected from USGS (United States Geological Survey) and USFWS (U.S. Fish & Wildlife Service). The overall protected area data was collected from USGS. I considered the national park and critical habitat data separately as some data were missing in the USGS protected area dataset. This ensures that all protected areas were excluded for SPV site selection analysis.

2. Specific Land use

Under the major specific land use criteria, we include urban/ residential areas, forest cover, and cultivated zones. Researchers (Anwarzai and Nagasaka, 2017; Merrouni et al., 2016; Castillo et al., 2016) have excluded these land covers as these are not suitable for solar panel development projects. Nevertheless, similar to protected areas, scholars have also focused on assigning a buffer zone to ensure the potentiality of SPV projects.

- (a) **Urban/ Residential Areas:** Since the 20th century urban growth has continuously been pushing cities further out. This urban extension is a continuous process with an increase in population, jobs, and opportunities (Glaeser and Kahn, 2004). Considering urban areas as a dynamic entity, the residential or urban areas have been excluded, as installing solar power plants adjacent to them could have a negative impact on the urban growth as well on the population residing there. Another concern over the distance from residential areas is the concept of community acceptance, which is designated as Not-In-My-Backyard (NIMBY). According to NIMBY, with decreasing proximity of residents to a renewable power, there is a corresponding escalation in opposition and unfavorable viewpoints (Hanger et al., 2016; Stephens et al., 2008). Following the previous literature, a buffer distance of 500m from the residential areas under exclusion boundary has been considered (Shorabeh et al., 2019; Sindhu et al., 2017; Zoghi, et al. 2017; Watson and Hudson, 2015; Uyan, 2013). I utilized NLCD (National Land Cover Data) for 2022 with a 30m resolution to exclude the urban areas from our study areas.

- **Forest Cover:** Forested landcover has also been eliminated from our study as it plays a significant role in maintaining our ecological balance. Installing a solar panel amid forest would pose potential threats to the forest ecosystem and biodiversity (Shorabeh et al., 2019; Solangi et al., 2019). All deciduous, evergreen, and mixed forests have been eliminated from our study area to avoid potential deforestation. The data has been extracted from 2022 NLCD (National Land Cover Data) layer.
- **Cultivated Areas:** A major focus of our research is to investigate landcovers that are not associated to the agricultural/ cultivated areas. Researchers, for instance, Watson and Hudson (2015); Majumdar and Pasqualetti (2019) and Yushchenko et al., (2018) strictly prohibited the installation of any on-grid solar panel on prime agricultural lands. Identifying suitable areas for solar micro-grids that fall outside of the major crop covers is one of our cardinal targets. I excluded some specific crop from the study area, (a) Corn, (b) Cotton, (c) Sorghum, (d)Soybeans, (e) Sunflower , (f) Sweet Corn , (g)Barley, (h) Spring Wheat, (i)Winter Wheat, (j) Canola, (k) Alfalfa, (l) Dry Beans, (m)Peas, and (n) Double Crops: WinWht/Corn, Barley/Corn, WinWht/Cotton, Soybeans/Oats, Corn/Soybeans, Barley/Soybeans. The data has been collected from USDA 2023 Crop Data layer. Through the omission of these particular crop data layers, my intention is to prevent any potential impact on valuable agricultural land, thereby directing our attention towards utilizing less productive lands as an alternative.

3. Disaster Risk zone

The exclusion criteria encompass various environmental factors, including risk-prone areas like floodplains, landslide-prone regions, and wind-exposed zones, as well as geological attributes incompatible with photovoltaic panel installation (Kengpol et al., 2012; Majumdar and Pasqualetti, 2019). Thus, we excluded flood susceptible areas that are incompatible with the installation of SPVs. The data has been collected from Kansas Applied Remote-Sensing (KARS) GeoPlatform. The dataset includes 2-foot contours sourced from the inundation map library of eastern Kansas. These values indicate the depth above the local water level and are derived through the FLDPLN (Floodplain) model which is convenient for rapidly estimating flood boundaries at specific depth levels.

4. Infrastructures

The presence of infrastructure or development areas has the potential to compromise the effectiveness of solar photovoltaic systems (SPVs) (Guaita-Pradas et al., 2019; Sánchez-Lozano et al., 2015; Sánchez-Lozano et al., 2014; Uyan, 2013). Thus, all military installations, airports and roads have been excluded under this broad criterion. Moreover, following Uyan (2013), I have considered a 500m buffer zone around the military areas as restricted. Data for military zones have been obtained from USGS. Subsequently, all airports have been excluded from the study area. Researchers have also considered a buffer distance of 3000m (Sun et al., 2021) for large scale SPV site selection around airports. However, as my thesis preponderantly focuses on micro-grid SPV panels, I followed the regulations/restrictions on distance to airport published by National Renewable Energy Laboratory (NREL) (Kandt and Romero, 2014). According to this report, it's allowed to install a SPV inside the airport boundary with a certain distance restriction to avoid solar glint or glare. However, due to technical measurement I adopted a buffer of 100m

adjacent to airports for SPV site selection analysis. Moreover, Nagasaka (2017) never mentioned a dedicated buffer distance even for a utility scale solar panel. I utilized the USGS National Transportation Dataset (NTD) to extract all airports and airport runways for Kansas. Lastly, even though connectivity is important, installing a SPV on the road is not feasible. Moreover, if a SPV is very close to the road, it has a potential risk to be damaged by vehicles (Abdulaziz et al., 2022). Thus, I consider having a 100m buffer of road area (Abdulaziz et al., 2022; Uyan, 2013) as unsuitable.

5. Waterbodies

All rivers, lakes, wetlands, and dams have been excluded from the study area, hence it's not feasible to install a micro-grid SPV on these land covers (Majumdar and Pasqualetti, 2019; Uyan, 2013). We excluded all wetlands and portable playas for our analysis. All open water (including rivers and wetlands) data has been derived from the NLCD data. I have also considered a 200m buffer distance (Majumdar and Pasqualetti, 2019) around waterbodies. Moreover, I also considered restricting probable playas, as according to US EPA playas are circular indentations in the ground, a distinctive feature of the Southern High Plains in the United States. They remain active only for a certain period, mostly after spring rainstorms. They are crucial for biodiversity as well. Thus, I assumed that they are unsuitable for solar PV installations due to their fluctuating water levels and unpredictable flooding risks. The data for probable playas are acquired from the Kansas Applied Remote Sensing (KARS) Program of the Kansas Biological Survey.

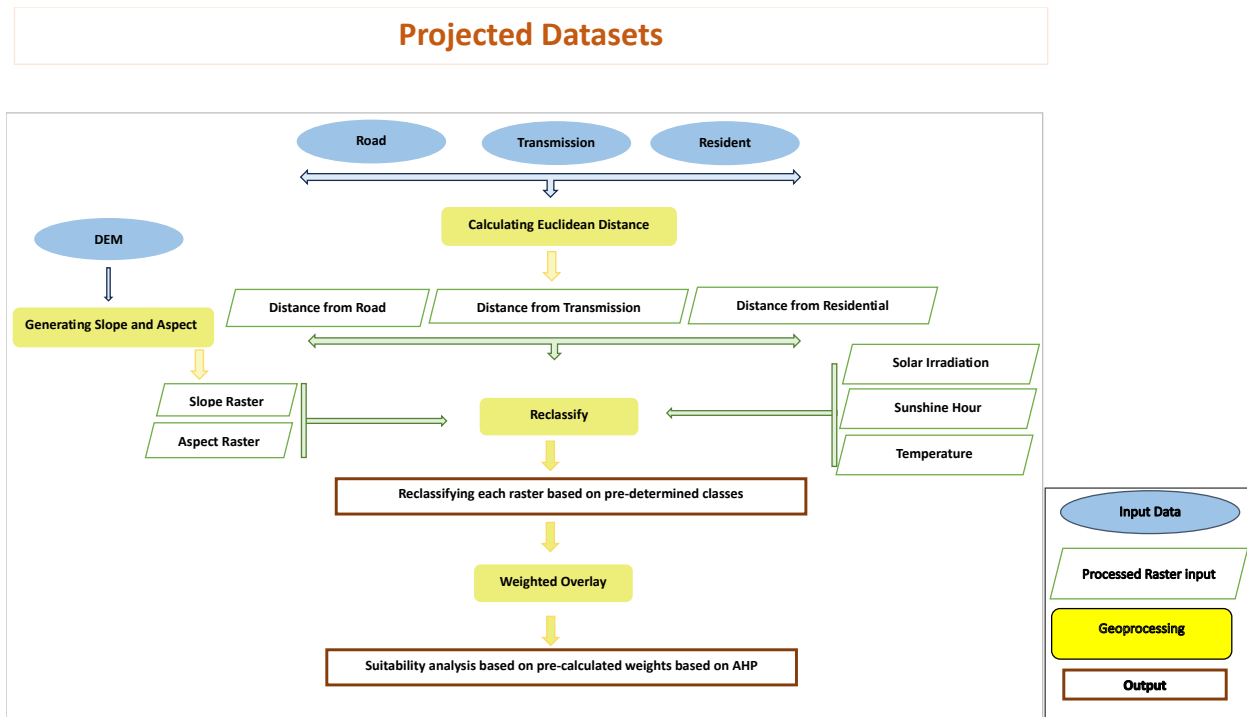
6. Slope

The significance of slope in solar power plant site selection is rooted in the considerable costs associated with building on steep terrains. As a result, areas with flat

or gently sloping landscapes are deemed more suitable. This becomes especially crucial for large-scale photovoltaic (PV) installations, where flat expanses are indispensable. Consequently, regions characterized by high slopes, such as steep lands and valleys, are advised to be excluded from consideration (Shorabeh et al., 2019; Al Garni and Awasthi, 2017). The literature lacks consensus on the acceptable slope percentage for SPV installations. Various studies propose different thresholds: Uyan (2013) excluded lands with slopes steeper than 3%, Charabi and Gastli (2011) went up to 5%, Watson and Hudson (2015) extended up to 10%, and Noorollahi et al. (2016) set the limit at 11%. Adhering to the guidance provided by Noorollahi et al. (2016) and Baban & Parry (2001), we established the threshold for excluding slopes at 10%. Through the utilization of Digital Elevation Models (DEMs), a comprehensive topographic analysis of the slopes has been generated within the study area. Notably, the DEM dataset employed for this purpose was acquired from the United States Geological Survey (USGS), offering a resolution of 10 meter.

3.3.5 Selection criteria analysis

I have selected eight site selection criteria to identify potential SPV sites in Kansas. These criteria were processed by utilizing several geoprocessing tools in the ArcGIS Pro platform. A framework containing the geoprocessing steps and pertinent output has been portrayed in Figure 3.5. Each of these criteria and associated geoprocessing steps are elaborately explained in the following section.



(a) Locational Criteria

1. Distance from Roads

Under this criterion, I attempt to determine the best location for solar photovoltaics in the context of the distance from the roads, owing to the importance of accessibility in deploying a solar project. The presence and accessibility of transportation routes plays a significant role by (a) avoiding cost associated to new transportation route construction, and (b) connecting regions in the process of transporting materials required for SPV installation.

Nevertheless, ensuring a safe distance from road is necessary to avoid road accidents and other security concerns (Alhammad et al., 2022). Thus, I considered 100m as restriction criteria and excluded the areas close to roads. However, after conducting a thorough literature review, we found no specific distance that can be universally considered optimal for solar photovoltaic installations. Hence, research conducted by Noorollahi et al. (2016) was considered as a

benchmark for establishing specific distances. Moreover, the decision of ranking the most to least suitable distance was informed by comparing with multiple prior studies and resemblance between the geographic characteristics of the area investigated (Ignizio, 2010). The data for primary transportation networks was collected as vector dataset from USGS National Transportation Dataset or NTD. The road data was processed in ArcGIS Pro by performing the “Euclidean distance” tool using the ArcGIS Spatial Analyst.

The locations based on proximity to roads were ranked in five classes, ranging from 0.0621371 miles or 100m to 5 miles or 8,047meters. Detailed information on the output produced by reclassifying the road data in ArcGIS Pro is shown in table 3.12.

Table 3.12: Outputs from ArcGIS Pro distance to road reclassification

Distance to roads (in meter)	Distance to roads (in miles)	Rank
100- 1,609	0.06-1	1 (Most suitable)
1,609 – 3,219	1-2	2
3,219 – 4,828	2-3	3
4,828 – 6,437	3-4	4
6,437 – 8,047	4-5	5 (Least Suitable)

2. Proximity to transmission lines

Another significant criterion in deploying an efficient solar photovoltaic sites is to site it in proximity to existing transmission lines. This criterion can simultaneously be considered as locational and economical. Aside from requiring a high cost to construct new transmission lines, the existing transmission lines also ensure network security, accessibility, and reliance. Thus, researcher have emphasized minimizing the distance of new SPV sites to existing transmission lines (Alhammad et al., 2022; Colak et al., 2020; Solangi et al., 2019; Koc et al., 2019; Sabo et al., 2019; Sindhu et al., 2017; Zoghi et al., 2017; Noorollahi et al., 2016; Castillo et al., 2016). Most researchers suggested 0-3 miles as the best distance (Noorollahi, 2016) while some strictly

prohibited distance more than 10 miles for SPV deployment (Ignizio, 2010). Data related to major transmission lines were collected from Homeland Infrastructure Foundation-Level Data (HIFLD) & GeoPlatform ArcGIS Online. By utilizing ArcGIS Pro platform, we calculated and divided the straight-line distance into five classes depending on the distance from each cell to the nearest existing transmission line (Table 3.13). Land parcels situated more than 12 miles away from transmission lines were deemed inaccessible from transmission line and thus were assigned a 5.

Table 3.13: Outputs from ArcGIS Pro distance to transmission line reclassification

Distance to transmission line (in meter)	Distance to transmission line (in miles)	Rank
0 - 4,828	0-3	1(Most suitable)
4,828 - 9,656	3-6	2
9,656 - 14,484	6-9	3
14,484 -19,312	9-12	4
19,312 meters and beyond	>12	5 (Least suitable)

3. Distance to urban areas

Developing solar panels close to urban or residential areas can give rise to opposition from residents (Colak et al., 2020; Uyan, 2013). Thus, in my research, a buffer of 500 from the urban/residential areas was masked from the study area. While it's important to maintain a suitable distance from residential areas, they should also be close enough to be able to fulfill energy demand of the residents (Colak et al., 2020). I followed the recommendation of Colak et al. (2020) and calculated the distance from residential areas by utilizing ArcGIS Pro platform. The urban/residential land cover data was extracted from USDA CDL (Cropland Data Layer) with a spatial resolution of 30m. After assessing the distance of urban areas to the nearest cell, I reclassified and scored them from 1(most suitable) to 5 (least suitable) as shown in Table 3.14.

Table 3.14: Outputs from ArcGIS Pro distance to residential areas reclassification

Distance to residential areas (in meter)	Distance to residential areas (in miles)	Rank
500-2000	0.31-1.24 miles	1(Most suitable)
2000 to 4000	1.24-2.49 miles	2
4000 to 6000	2.49-3.73 miles	3
6000 to 8000	3.73-4.97 miles	4
8000 meters and beyond	4.97-and beyond miles	5 (Least suitable)

(b) Orographic Criteria

4. Slope

Most development projects seek locations with gentle slope that can help avoid costs associated to earthmoving and site preparation (Yesilnacar et al., 2012; Çetinkaya et al., 2016; Atici et al., 2015; Gigović et al., 2016; Sánchez-Lozano et al., 2014). Places with steep slopes require higher cost to deploy SPV. Thus, most researchers have avoided a specific percent rise of slope to minimize construction costs.

We obtained a Digital Elevation Model (DEM) from USGS to generate a slope map for the state of Kansas. All areas exceeding a slope of more than 10% were excluded. Based on previous published work on solar photovoltaic site selection we ranked slope values of 1% or less as the highly suitable sites (Alhammad et al., 2022; Noorollahi et al., 2016; Ignizio, 2010). The complete list of slope reclassification is provided in Table 3.15.

Table 3.15: Outputs from ArcGIS Pro slope reclassification

Slope (%)	Rank
<1	1(Most suitable)
1-2	2
2-3	3
3-4	4
4-10	5 (Least suitable)

5. Aspects

While slope explains the steepness of a surface, aspect defines the orientation of that slope with respect to the sun. Aspect is measured in degrees and can be generated from a Digital Elevation Model. In ArcGIS Pro, the “Aspect” tool provides the orientation of a land surface based on the provided DEM data. An aspect map may include several orientations, for instance, North, Northeast, Northwest, East, West, Southwest, Southeast, and South. The southern direction receives the most solar radiation; and is considered as the best orientation to install solar photovoltaic panels (Doljak and Stanojević, 2017). Following south, the orientations southwest and south-east are ranked second and East and West are ranked third, respectively (Table 3.16).

Table 3.16: Outputs from ArcGIS Pro aspects reclassification

Aspect (Slope Orientation)	Rank
South	1(Most suitable)
Southeast and southwest	2
East and West	3
Northeast and Northwest	4
North	5 (Least suitable)

(c) Climatic criteria

6. Solar Irradiation

Solar irradiation is one of the most significant factors in determining optimal location for SPV. It helps determine areas with the sunniest conditions that can be appropriate for SPV. The observed positive relationship between solar irradiation and SPV electricity generation motivates investors to install PV power plant areas that receive high solar insulation (Akkas et al., 2017). To be economically efficient, a solar project requires a minimum solar radiation of 3.5

kWh·m⁻²·day⁻¹ (Kiatreungwattana et al., 2013), However, if the solar irradiation exceeds 5.48 kWh·m⁻²·day⁻¹, a slight decrease in the efficiency of solar PV system might arise (Quaschnig, 2004).

For this research, a globally recognized measure, the Global Horizontal Irradiation or GHI was utilized. GHI (KWh/m²) is calculated as the aggregate of direct and scattered solar radiation and deemed essential for evaluating solar PV/flat-plate photovoltaics potential (Prăvălie et al., 2019). The raster data for GHI has been obtained from Global Solar Atlas, which is a long-term yearly average of daily global horizontal irradiation covering the period 1999-2018. Based on previous research, the solar insolation values were organized into five separate classes in table 3.17.

Table 3.17: Outputs from ArcGIS solar irradiation reclassification.

GHI (KWh/m ² / day)	Rank
4.253- 4.564928	5 (Least suitable)
4.564928 -4.701941	4
4.701941 - 4.821963	3
4.821963 - 4.952006	2
4.952006 - 5.145	1 (Most suitable)

7. Average Annual Temperature:

There is an inverse relationship between the efficacy of solar photovoltaics and ambient temperature. In a study conducted by Libra et al. (2021) with a focus on effects of cell temperature, a declining efficiency of PVs occurs with increase in temperature. According to Huld and Gracia (2015) and Yelmen and Çakir (2016), an increase of 1°C temperature above 25°C, results in a decline in efficiency of solar photovoltaics by approximately 0.4%–0.5%. Furthermore, increasing ambient temperature necessitates cooling systems which therefore decreases the efficiency of solar photovoltaics. Thus, areas with lower temperatures are most

suitable for SPV deployment. Average annual temperature data has been derived from PRISM Climate Group with a spatial resolution of 800m. The PRISM 30-Year Normal data covers average monthly and annual temperature for a time span of 30 years (1991-2020). This 30-year grid data was further reclassified into five classes based on solar photovoltaic site suitability (Table 3.18).

Table 3.18: Outputs from ArcGIS Pro annual temperature reclassification

Temperature (°C)	Rank
10 - 11	1
11-12	2
12-13	3
13-13.5	4
14 and beyond	5

8. Sunshine Hour

Sunshine hour is another significant climatological parameter that calculates the amount of solar energy for a particular area. Data pertinent to solar sunshine hours have been derived from NASA POWER, a solar and meteorological database. NASA POWER provides 30-year (1991-2019) annual average sunshine hour data for 160 stations in Kansas. This data was interpolated using a kriging method in ArcGIS Pro interface. Kriging is a geostatistical method that interpolates a raster based on geospatial point data representing sunshine hours. I employed an ordinary kriging method to predict and create a raster surface of sunshine hour for the state of Kansas. The output raster has been reclassified into five classes from best to least in terms of solar photovoltaic site suitability (Table 3.19).

Table 3.19: Outputs from ArcGIS Pro sunshine hour reclassification

Sunshine Hour	Rank
12.046179 - 12.048216	5
12.048216 - 12.049696	4
12.049696 - 12.050771	3
12.050771 - 12.052032	2
12.052032 - 12.053768	1

3.3.6 Sensitivity analysis

Sensitivity analysis in multicriteria decision analysis is a widely used method to test the robustness of proposed model against changes (Zheng et al. 2016). This analysis plays a crucial role in providing comprehensive knowledge of probable change in decision making owing to the difference in expert's opinion. It hypothesizes that changes in experts' opinion could end up providing markedly different output. Thus, I conducted a macro-scale (state-based) sensitivity analysis to identify how changing the extent of selection criteria influences the final SPV site selection.

The sensitivity analysis was conducted on three major site selection criteria and their sub-criteria. These categories are locational (i.e., distance from road, transmission line, and residential area), orographic (i.e., slope and aspects), and climatic (i.e., solar irradiation, temperature, and sunshine hour). The sensitivity analysis focused on three scenarios including: Location-centric scenario (S1), Climate-centric scenario (S2), and an Orography-centric scenario (S3).

Three additional consistency matrices were produced by assigning most weight (scale of 9) to the criteria under a particular category. For instance, in terms of Location-centric scenario (S1), a scale of 9 was assigned to distance from road, transmission line, and residential area

compared to other sub-criteria. This consistency ratio will provide different weights for each criterion under a particular category. The maximum number of pixels in the most suitable class reflects the substantial impact of the corresponding category (or sub-criteria). To evaluate the potential sensitivity of these criteria, an overlay analysis was utilized to produce three maps based on each scenario. These outputs analyze the changes in most suitable areas for each of the sensitivity scenario to show the existing uncertainties in site selection criteria.

3.4 Result and Discussion

To better understand and comprehensively portray the result of analysis, all restriction and site selection criteria are visually represented in maps. The final output will be represented as an unsuitable map combining areas that are unsuitable for solar site selection. These areas encompass protected areas, disaster prone zones, unsuitable steep slope regions, urban, agricultural, and forested regions, and lastly all waterbodies. This process ensures that all restricted regions are separated for the next step to identify suitable SPV sites within the State of Kansas.

For the second step each criterion was indexed and classified into five levels (very high suitability, high suitability, moderate suitability, low suitability, and least suitability) by utilizing an equal intervals reclassification in GIS. These maps will be integrated to conduct an overlay analysis by using the weighted factor resulted from analytical hierarchy processing analysis. The overlay analysis will generate an integrated map to show suitable solar PV site selection in Kansas by considering locational, orographic, and climatic criteria.

3.4.1 Constraint criteria mapping

Figure 3.6 displays a map showing the distribution of all protected areas, infrastructures, restricted land cover types, waterbodies, flood risk zone, and unsuitable slope for SPV development in Kansas. Following the framework in Figure 3.4 the restriction criteria have been merged and overlayed to remove them from the study area.

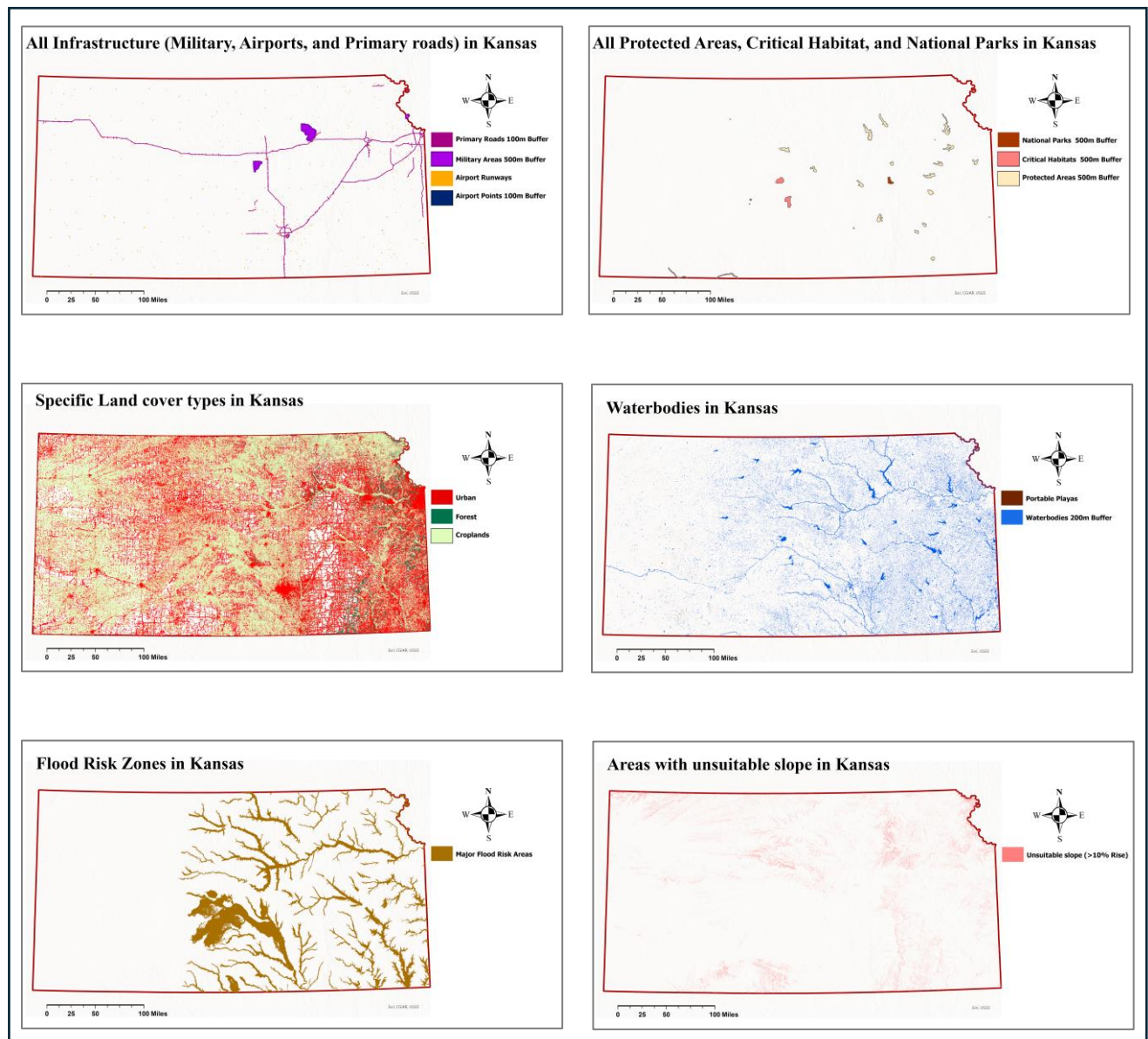


Figure 3.6: Maps representing unsuitable/restricted areas for SPV deployment in Kansas.

The restricted land cover in Kansas covers approximately 14.29 million hectares or 35,310,317.84 acres. Approximately 67.06 percent of areas of Kansas are unsuitable for solar photovoltaic projects. However, this research only considers suitable SPV site selection for marginal lands, all restricted landcover have been eliminated. After removing all restriction criteria from marginal lands, I identified only 0.714% of Kansas, which is approximately 152,702.28 hectares, as suitable for solar photovoltaic development. This will ensure identifying locations where SPV will have minimal social, economic, and environmental impact. A map has been produced to show the land parcels that will be utilized for the further spatial processing to identify the best and least suitable site for SPV projects (Figure 3.7).

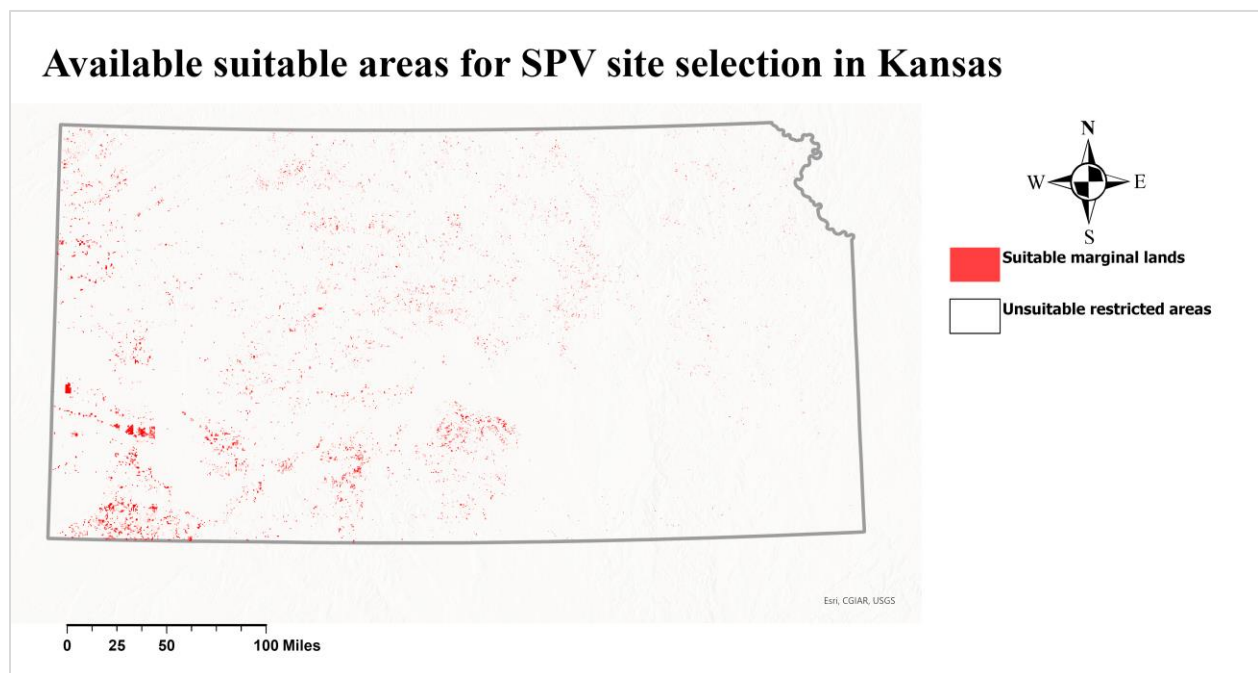


Figure 3.7: Available marginal lands for SPV site selection process.

3.4.2 Selection Criteria Analysis

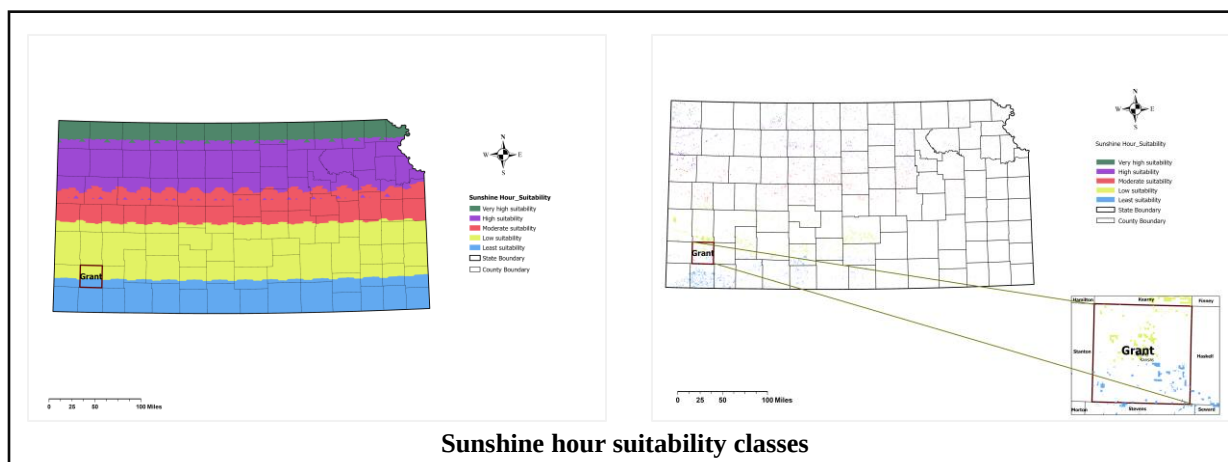
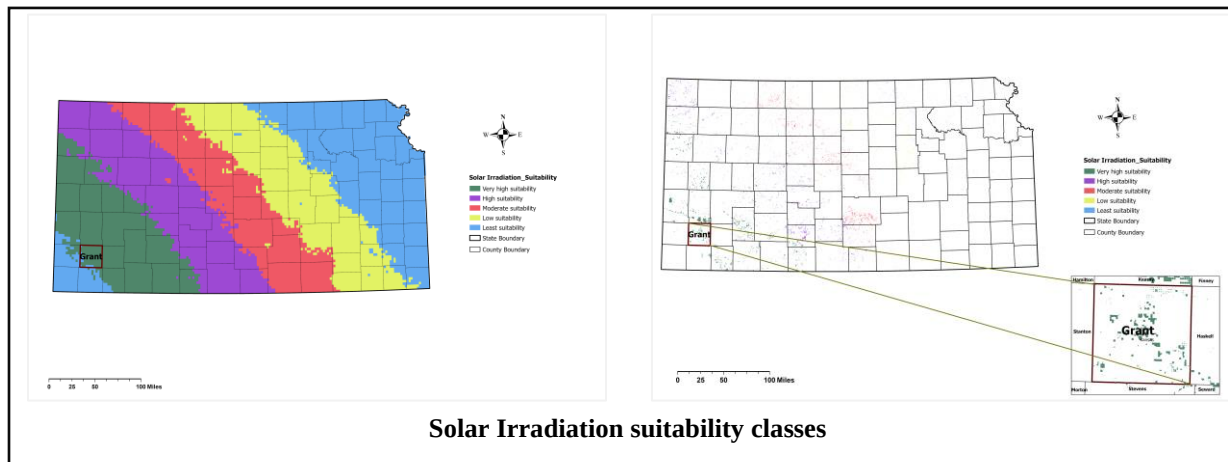
Only 1.64% of marginal lands are identified as suitable for SPV deployment in Kansas. However, the suitability of these land covers depends on several site selection criteria (and sub-criteria), for instance, locational climatic or orographic. The sub criteria have been reclassified based on previous research conducted on SPV site selection. The process of reclassifying these sub-criteria has been conducted on marginal lands that have been comprehensively discussed in chapter two. Thus, the processing of all these sub-criteria is restricted to small parcels of marginal lands delineated by the CLU boundaries. An overview of these criteria (and sub-criteria) for (a) entire state of Kansas and (b) masked to marginal lands in Kansas has been depicted below. These illustrations will provide an overall distribution of site selection criteria at a large scale as well as small common land unit scale.

3.4.2.1 Climatic criteria

Figure 3.7 provides a spatial distribution of Global Horizontal Irradiance (GHI) in Kansas. Solar irradiance increases as we move from the east to the western side of Kansas. Roughly 17.09% ($36,513.80 \text{ km}^2$ / 3.65138 million hectares.) of Kansas receives GHI over $4.95 \text{ kWh} \cdot \text{m}^{-2} \cdot \text{day}^{-1}$, making it one of the highest solar irradiation areas in the world (Právělie, et al., 2019). Additionally, about 38% of Kansas is classified as very suitable to suitable for solar energy generation based on this criterion. The lowest solar irradiance values are found in the eastern part of Kansas. When looking at marginal land cover in Kansas, approximately 60% (approx. 1618 km^2 / 0.1618 million hectares) of the total marginal lands are classified as very highly suitable (35.3%) to highly suitable (25.04%) based on this criterion. This suggests a high potential for Solar Photovoltaic (SPV) projects on the marginal lands in Kansas.

The amount of sunshine hours is an important climatic factor which is highly correlated with solar irradiation. In Kansas, there is minimal variation in sunshine hours across the state. However, the northern part of Kansas generally experiences more sunshine hours than the southern part (Figure 3.8). It is estimated that only 6.35% (190 km²/ 0.019 million hectares) of the total marginal land cover in Kansas has the highest sunshine hours.

The last sub-criterion under the climatic criteria is average annual temperature. No abrupt change in temperature has been observed in the study area. Moving from south to north an increase in temperature has been observed (Figure 3.8)



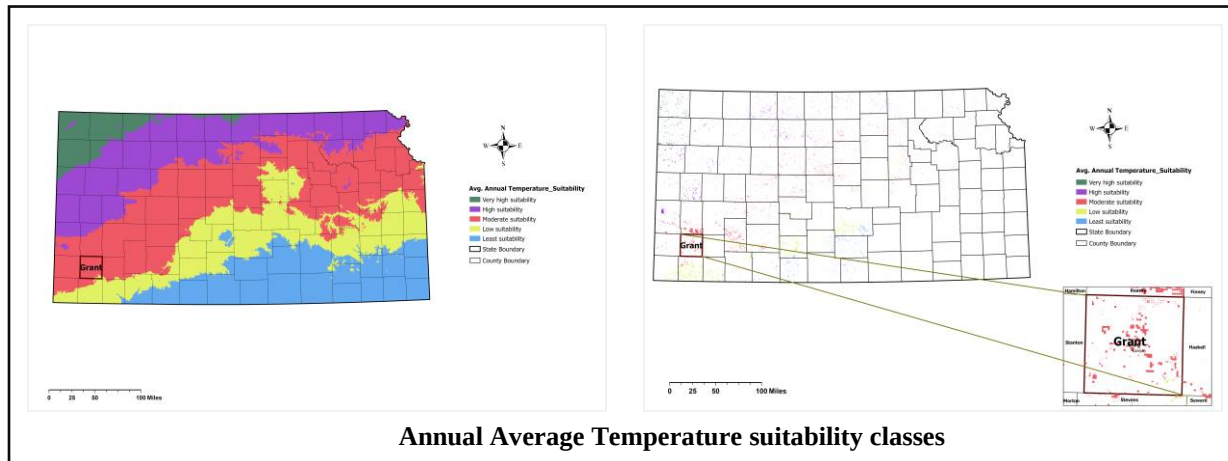


Figure 3.8: Distribution of climatic criteria suitability classification

3.4.2.2 Orographic criteria

It has been observed that more than 90% (206,510 km²/ 20.651 million hectares) of Kansas has a slope of less than 10 % rise. Marginal land with a slope more than 5% rise are considered as restricted for SPV site suitability assessment (Figure 3.8). Consequently, an area of 1789 km²/ 0.1789 million hectares (60% of total marginal lands identified) has been recognized as very high to highly suitable areas that possess the potential to be utilized for SPV projects. Additionally, the orientation of slopes, specifically south facing slopes, is considered most feasible for SPV, covering about 10% of the total marginal land in Kansas (Figure 3.9).

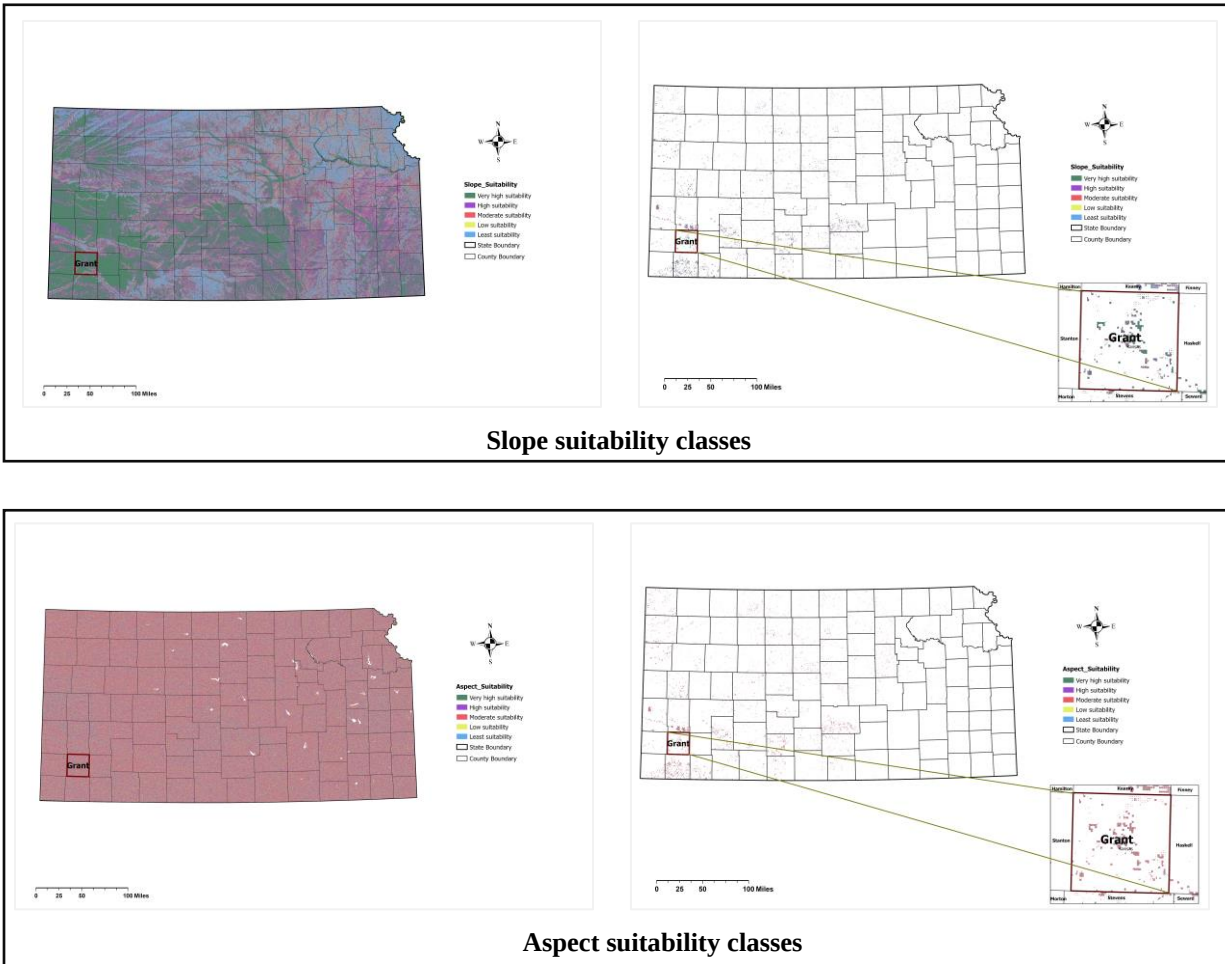


Figure 3.9: Distribution of orographic criteria suitability classification

3.4.2.3 Locational criteria

The proximity to transmission lines, roads, and residential areas carries significant weight in this analysis. Proximity to transmission lines is one of the most important criteria for selecting on-grid solar photovoltaic (SPV) sites. Closer proximity to transmission lines reduces the economic costs associated with SPV deployment. On the other hand, locations farthest from town or residential areas are considered the least suitable for SPV projects. Equal accessibility to roads has been observed in all counties in Kansas. A major portion of Kansas is located in close proximity to roads, making it highly suitable for SPV projects. Furthermore, the western part of Kansas shows high suitability in terms of proximity to residential areas compared to the eastern

side of Kansas. In Figure 3.10, a reclassified map of all locational criteria has been illustrated for Kansas as a whole and for marginal lands.

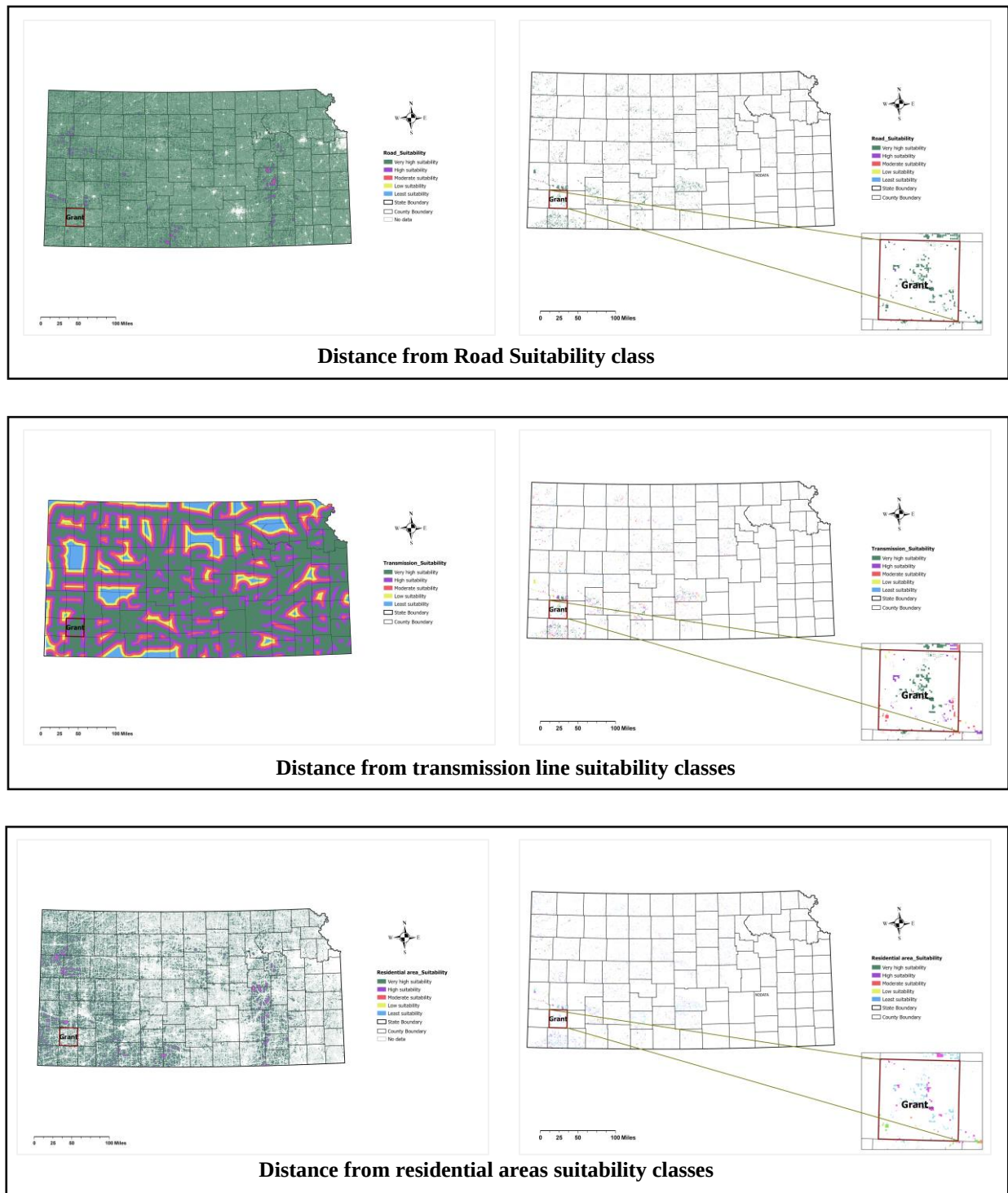


Figure 3.10: Distribution of Locational criteria suitability classification

3.4.3 AHP consistency check and weight assignment

The calculated consistency ratio (CR) for the expert opinion survey is 0.05 which reflects that the result is satisfactory and reliable. Moreover, this consistency also depicts that the weights estimated by this process can be used for further processing in GIS interface. The calculated weights of the eight selection criteria and their consistency indices are presented in Table 3.20.

Table 3.20: Calculated consistency matrix and weights for each sub-criteria.

Criteria	Solar Irradiance	Sunshine Hour	Distance from Transmission Lines	Proximity to Transportation Routes	Distance from Residential Areas	Temperature	Slope	Aspects	Criteria weight
Solar Irradiance	0.258	0.227	0.205	0.356	0.218	0.274	0.347	0.335	0.277
Sunshine Hour	0.240	0.211	0.179	0.207	0.206	0.258	0.212	0.217	0.216
Distance from Transmission Lines	0.179	0.156	0.132	0.114	0.124	0.064	0.102	0.092	0.120
Proximity to Transportation Routes	0.035	0.031	0.055	0.048	0.056	0.060	0.045	0.059	0.049
Distance from Residential Areas	0.116	0.161	0.105	0.084	0.098	0.037	0.090	0.095	0.098
Temperature	0.039	0.034	0.085	0.023	0.110	0.042	0.027	0.028	0.049
Slope	0.067	0.090	0.117	0.098	0.100	0.137	0.091	0.090	0.099
Aspects	0.066	0.090	0.123	0.070	0.088	0.128	0.087	0.085	0.092

Based on the resultant consistency matrix, the most significant criteria for SPV site selection are, solar irradiation, sunshine hour, distance from transmission line, distance from

residential area, and slope, with the weightings of 28%, 21%, 12% 10%, and 10% respectively.

Table 3.21 shows the classes and associated grades that have been assigned to each criterion.

Table 3.21: SPV criteria and sub-criteria weight distribution and grading

Criteria Weight	Criteria	Sub criteria weight	Sub-criteria	Classes	Grades
54%	Climatic	28%	Solar Irradiation	4.253- 4.564928	5
				4.564928 -4.701941	4
				4.701941 - 4.821963	3
				4.821963 - 4.952006	2
				4.952006 - 5.145	1
		21%	Sunshine hour	12.046179 - 12.048216	5
				12.048216 - 12.049696	4
				12.049696 - 12.050771	3
				12.050771 - 12.052032	2
				12.052032 - 12.053768	1
		5%	Temperature	10 - 20	1
				20-25	2
				25-27	3
				27-29	4
				29-31	5
27%	Locational	5%	Transportation	100- 1609	1
				1,609 – 3,219	2
				3,219 – 4,828	3
				4,828 – 6,437	4
				6,437 – 8,047	5
		12%	Transmission line	0 - 4,828	1
				4,828 - 9,656	2
				9,656 - 14,484	3
				14,484 -19,312	4
				19,312 meters and beyond	5
		10%	Residential Areas	500-2000	1
				2000 to 4000	2
				4000 to 6000	3
				6000 to 8000	4
				8000 meters and beyond	5
19%	Orographic	10%	Slope	<1	1
				1-2	2
				2-3	3
				3-4	4
				4-10	5
		9%	Aspects	South	1
				Southeast and southwest	2
				East and West	3
				Northeast and Northwest	4
				North	5

3.4.4 Suitability Map

The GIS-based site suitability analysis aimed to identify the best locations for solar photovoltaic (SPV) sites in Kansas. After eliminating the restricted areas, it has been estimated that approximately 68% of total marginal lands of Kansas are unsuitable for solar photovoltaic development. Only 33% (1527.0228 square kilometers or 0.1527 million hectares) of total marginal lands in Kansas are considered suitable for further geospatial processing. These areas are classified into indicating five levels of suitability: very high, high, moderate, low, and least suitability and portrayed as a map in Figure 3.11.

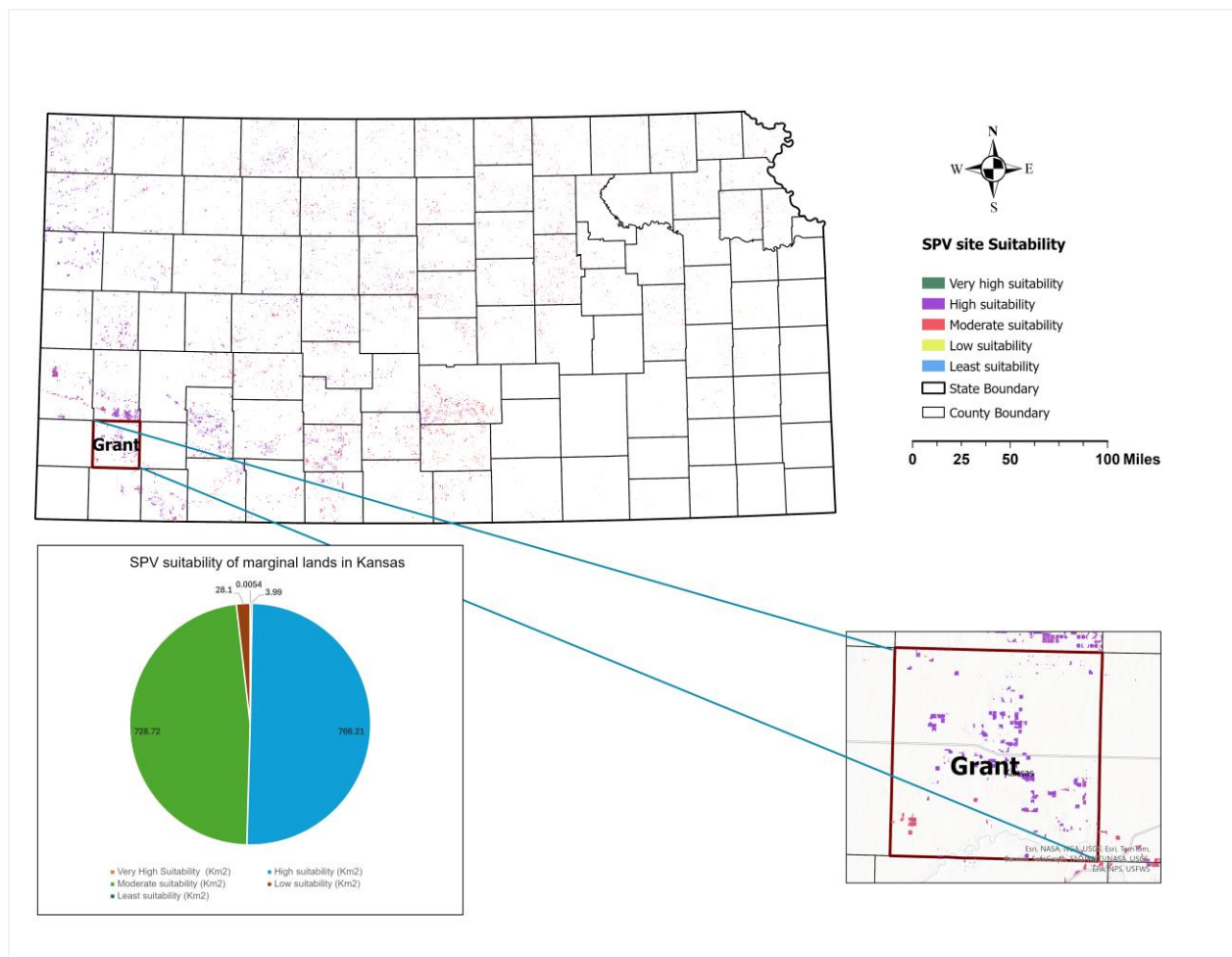


Figure 3.11: Optimal SPV sites for the marginal lands in Kansas using multicriteria decision model and AHP evaluation.

It is observed that the very high suitability and high suitability categories are distributed to specific areas in southwest Kansas, followed by moderate and other suitability levels (Figure 3.12).

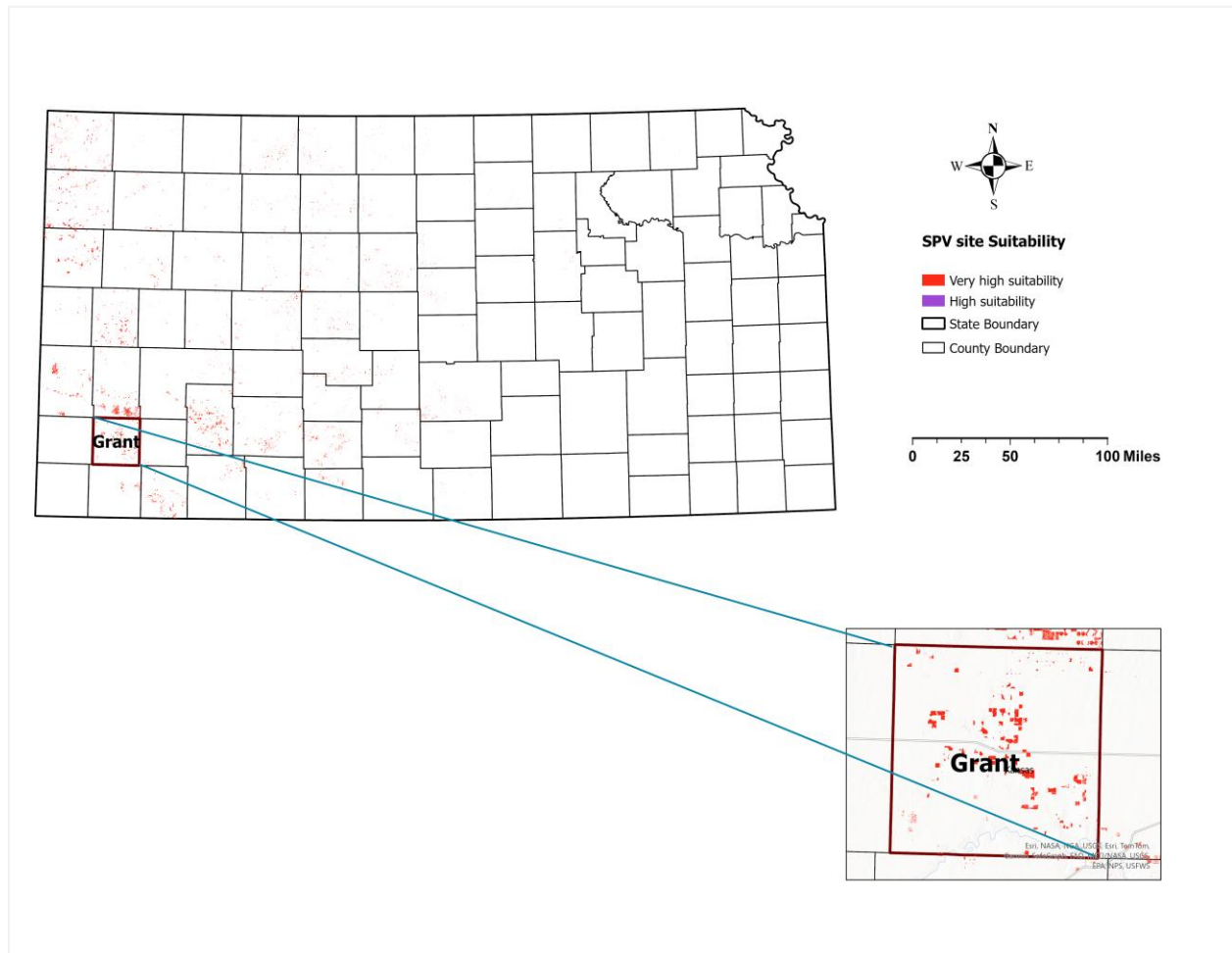


Figure 3.12: Very high and highly suitable SPV sites in Kansas.

This analysis demonstrates that only a fraction of marginal lands in Kansas (0.26%) can be considered as extremely suitable (Very high suitability) for SPV projects (Table 3.22). However, approximately 50% of total marginal lands are deemed as highly suitable, and 47.72% of suitable marginal lands in Kansas are considered moderately suitable for SPV development. Lastly, only 0.0004% of total marginal lands are listed as least suitable. This exhibits a high potential of marginal lands for future SPV deployment in Kansas.

Table 3.22: Areal distribution of marginal lands under five suitability ranks.

Very High Suitability (area in Km ²)	High suitability (area in Km ²)	Moderate suitability (area in Km ²)	Low suitability (area in Km ²)	Least suitability (area in Km ²)
0.26% (3.99)	50.18% (766.21)	47.72% (728.72)	1.84% (28.10)	0.0004% (0.0054)

To provide a rudimentary spatial distribution of SPV suitable sites on a county level, I calculated the mean suitability score for each of the 105 counties in Kansas. This provides rough insights on the most suitable counties for SPV deployment in Kansas. The processing has been conducted on the base/reference site suitability model. Figure 3. 13 displays the spatial distribution of mean suitability across the counties in Kansas. The map indicates that counties like Cheyenne, Sherman, Wallace, Greeley, Grant, and Gray are highly suitable whereas counties like Elk, Wilson, Bourbon, Labette are less suitable. Additionally, Morton and Butler counties appear to be unsuitable for SPV deployment.

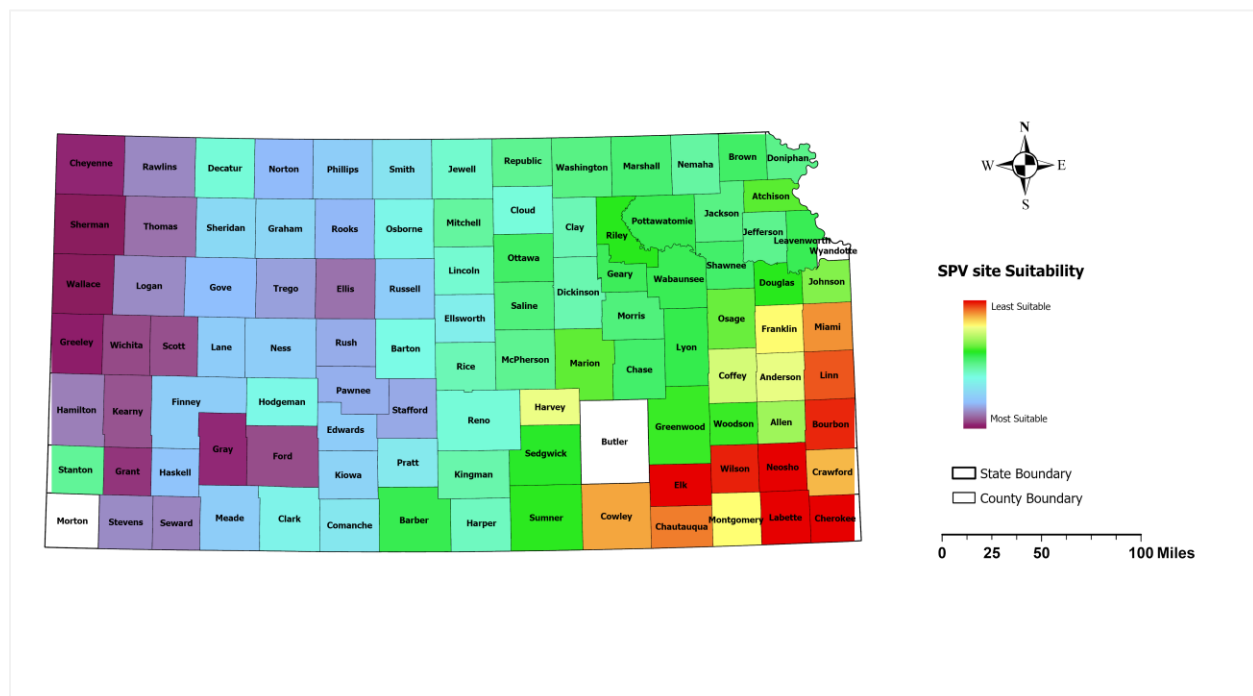


Figure 3.13: Result of zonal statistics of sit suitability across the counties in Kansas.

3.4.5 Sensitivity analysis result

Table 3.23, 3.24, and 3.25 presents pairwise comparison for: Location-centric scenario (S1), Climate-centric scenario (S2), and Orography-centric scenario (S3). These pairwise comparison matrices provide an estimation of weights for each criterion. A significant change in weights under the three scenarios was conducted. Table 3.26 comprises observed changes in weights under different categories.

Table 3.23: Pairwise comparison matrix and associated weight produced for Location centric scenario (S1)

Criteria	Solar Irradiance	Sunshine Hour	Distance from Transmission Lines	Proximity to Transportation Routes	Distance from Residential Areas	Temperature	Slope	Aspects	Criteria weight
Solar Irradiance	0.034	0.036	0.205	0.356	0.218	0.140	0.108	0.109	0.151
Sunshine Hour	0.031	0.033	0.179	0.207	0.206	0.132	0.066	0.071	0.115
Distance from Transmission Lines	0.304	0.299	0.132	0.114	0.124	0.191	0.254	0.251	0.209
Proximity to Transportation Routes	0.304	0.299	0.055	0.048	0.056	0.191	0.254	0.251	0.182
Distance from Residential Areas	0.304	0.299	0.105	0.084	0.098	0.191	0.254	0.251	0.198
Temperature	0.005	0.005	0.085	0.023	0.110	0.021	0.009	0.009	0.033
Slope	0.009	0.014	0.117	0.098	0.100	0.070	0.028	0.029	0.058
Aspects	0.009	0.014	0.123	0.070	0.088	0.065	0.027	0.028	0.053

Table 3.24: Pairwise comparison matrix and associated weight produced for Climate centric scenario (S2)

Criteria	Solar Irradiance	Sunshine Hour	Distance from Transmission Lines	Proximity to Transportation Routes	Distance from Residential Areas	Temperature	Slope	Aspects	Criteria weight
Solar Irradiance	0.258	0.227	0.290	0.253	0.284	0.274	0.285	0.282	0.269
Sunshine Hour	0.240	0.211	0.290	0.253	0.284	0.258	0.285	0.282	0.263
Distance from Transmission Lines	0.179	0.156	0.032	0.067	0.040	0.064	0.036	0.034	0.076
Proximity to Transportation Routes	0.035	0.031	0.014	0.028	0.018	0.060	0.016	0.022	0.028
Distance from Residential Areas	0.116	0.161	0.026	0.049	0.032	0.037	0.031	0.035	0.061
Temperature	0.039	0.034	0.290	0.253	0.284	0.042	0.285	0.282	0.188
Slope	0.067	0.090	0.029	0.057	0.032	0.137	0.032	0.033	0.060
Aspects	0.066	0.090	0.030	0.041	0.028	0.128	0.030	0.031	0.056

Table 3.25: Pairwise comparison matrix and associated weight produced for Orography centric scenario (S3);

Criteria	Solar Irradiance	Sunshine Hour	Distance from Transmission Lines	Proximity to Transportation Routes	Distance from Residential Areas	Temperature	Slope	Aspects	Criteria weight
Solar Irradiance	0.067	0.069	0.090	0.220	0.089	0.185	0.347	0.335	0.175
Sunshine Hour	0.062	0.064	0.078	0.128	0.084	0.174	0.212	0.217	0.127
Distance from Transmission Lines	0.047	0.047	0.058	0.071	0.050	0.043	0.102	0.092	0.064
Proximity to Transportation Routes	0.009	0.009	0.024	0.030	0.023	0.041	0.045	0.059	0.030
Distance from Residential Areas	0.030	0.049	0.046	0.052	0.040	0.025	0.090	0.095	0.053
Temperature	0.010	0.010	0.037	0.014	0.045	0.028	0.027	0.028	0.025
Slope	0.334	0.333	0.287	0.228	0.308	0.252	0.091	0.090	0.240
Aspects	0.441	0.419	0.380	0.257	0.361	0.252	0.087	0.085	0.285

Table 3.26: Changes in weight distribution under different scenarios of sensitivity analysis

Scenario	Original	S1	S2	S3
Location centric scenario (S1)	0.2673039	0.5893	0.1646	0.1470
Climate centric scenario (S2)	0.5419	0.2997	0.7201	0.3274
Orography centric scenario (S3)	0.1908	0.1111	0.1153	0.5257

Three different site suitability maps were produced based on the calculated weights produced under the three different sensitivity scenarios, i.e., location-focused, climate focused, and orography -focused. These maps are portrayed in Figure 3.14, 3.15, and 3.16. The output maps follow the same range of classes (Class 1: most suitable to Class 5: least suitable). The amount of pixels (or areas) has been calculated for each of the classes under these three categories. The surface area percentages estimated from this analysis have been compiled in Table 3.27. The base/reference site suitability area percentages have also been included to provide a comparison of all sensitivity scenarios.

Table 3.27: Total area percentage and descriptive summary of areas under three sensitivity scenarios

Scenario	Very High Suitability (area in Km ²)	High suitability (area in Km ²)	Moderate suitability (area in Km ²)	Low suitability (area in Km ²)	Least suitability (area in Km ²)
Base suitability	0.26% (3.99)	50.18% (766.21)	47.72% (728.72)	1.84% (28.10)	0.0004% (0.0054)
Location centric scenario (S1)	1.79% (27.33)	71.62% (1,093.63)	25.61% (391.01)	0.98% (15.01)	0.00% (0.04)
Climate centric scenario (S2)	0.48% (7.38)	35.01% (534.68)	60.46% (923.30)	4.03% (61.49)	0.01% (0.17)
Orography centric scenario (S3)	0.55% (8.37)	41.84% (638.94)	51.95% (793.34)	5.65% (86.31)	0.0037% (0.06)
	Total area in percentage (Km ²)				

From the analysis, it has been found that sub-criteria under S1 or Location-centric scenario are most sensitive to change. It has been justified by the highest variation in very high suitability and high suitability classes. Moreover, both very high and high suitability classes cover the majority of marginal land cover (approx. 73 %), as compared to the rest of the suitability classes. The suitability map under this sensitivity scenario is shown in Figure 3.14. It can be implied that if the locational criteria (especially distance from transmission line) are given most priority the distribution of suitable areas will drastically change.

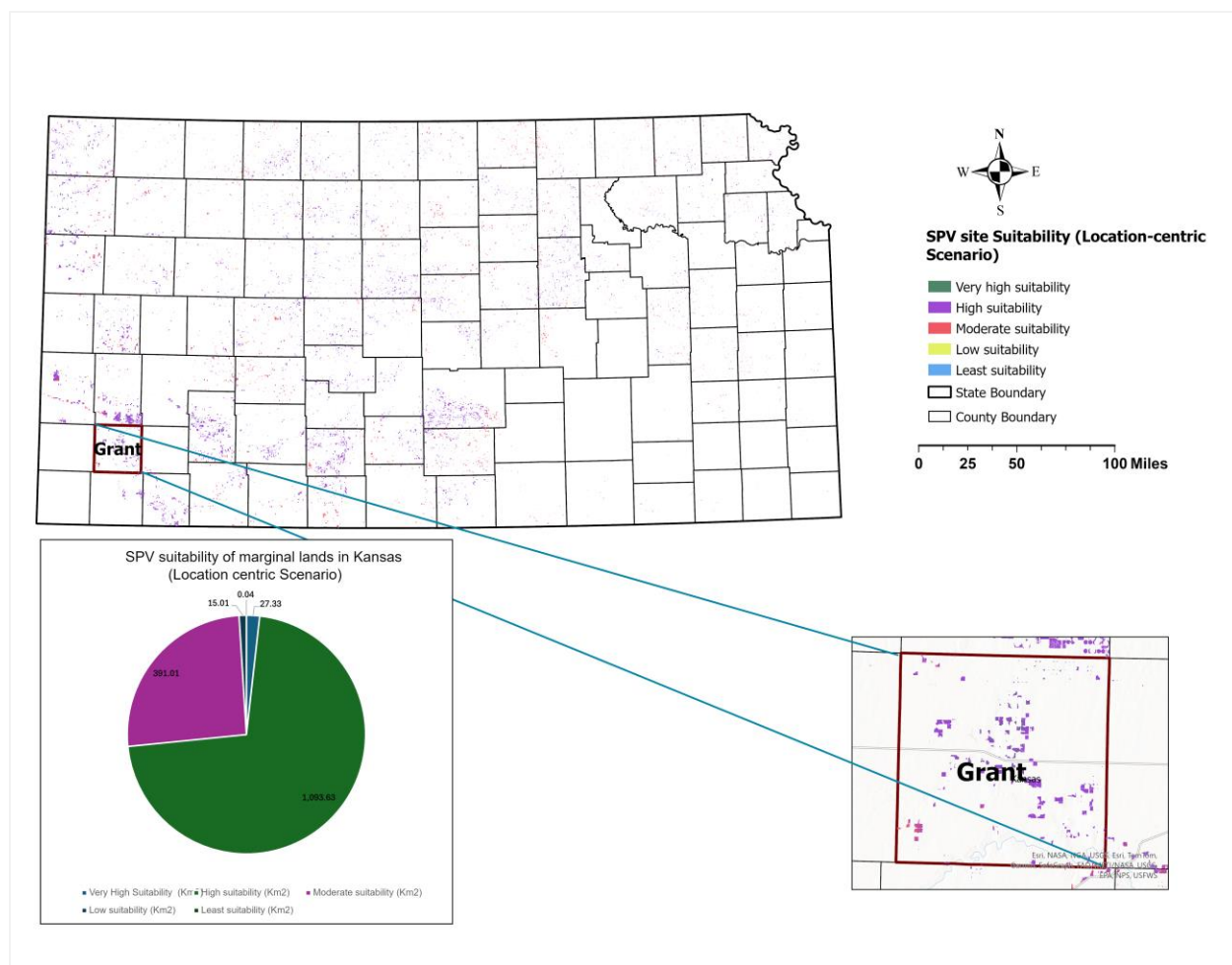


Figure 3.14: Sensitivity analysis : Location centric scenario.

The second most sensitive category that changes the distribution of suitable areas is climate-centric sensitivity (S2). An increase in very high (0.22%) suitability areas has been observed. Thus, the sensitivity analysis also indicates an increase in low suitability areas (Figure 3.15).

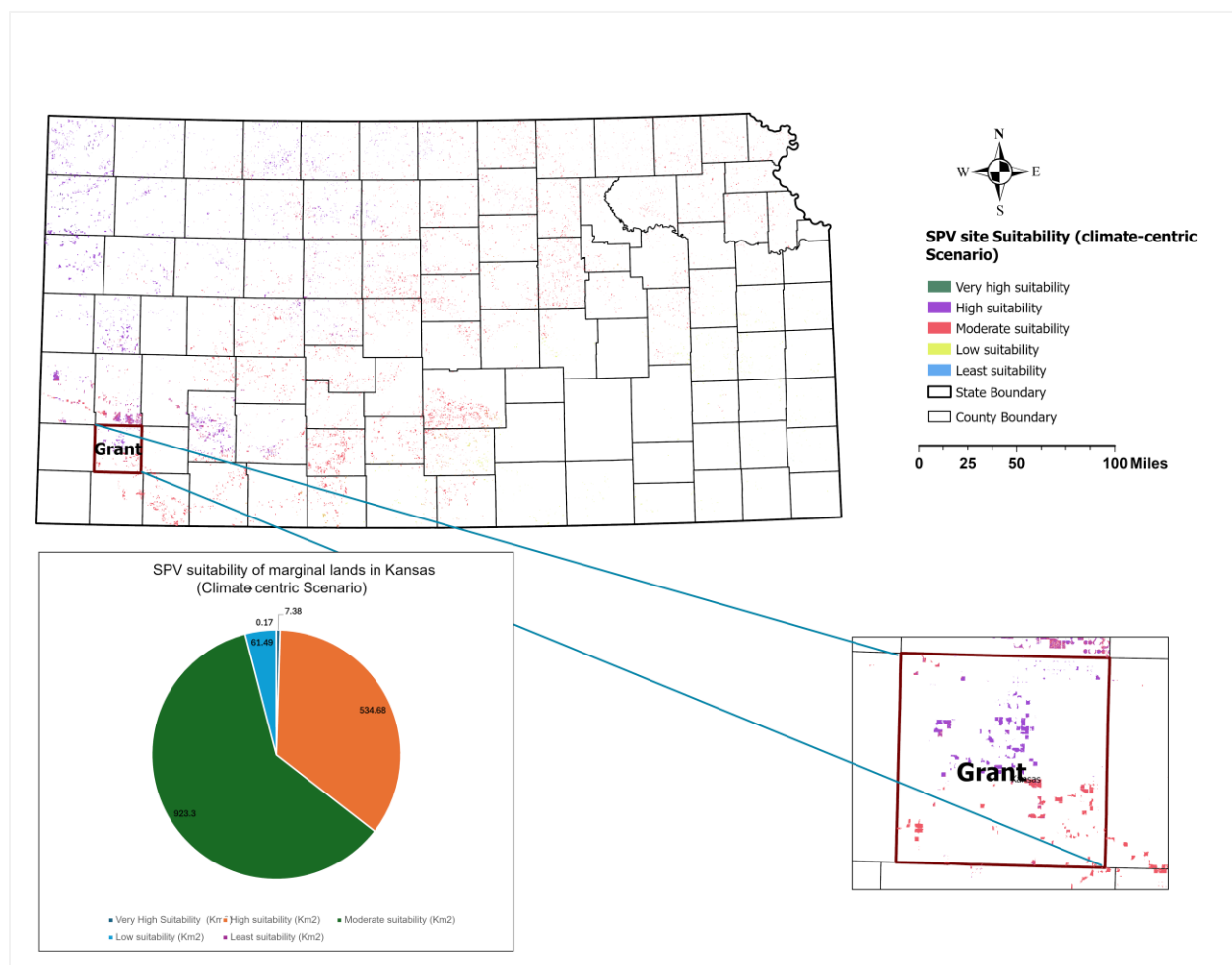


Figure 3.15: Sensitivity analysis: Climate centric scenario

The least sensitive category is orography-centric scenario (S3) which focuses on the changes in slope and aspects values. A slight increase in very high suitability class (0.29%) has been observed under this sensitivity model (Figure 3.16).

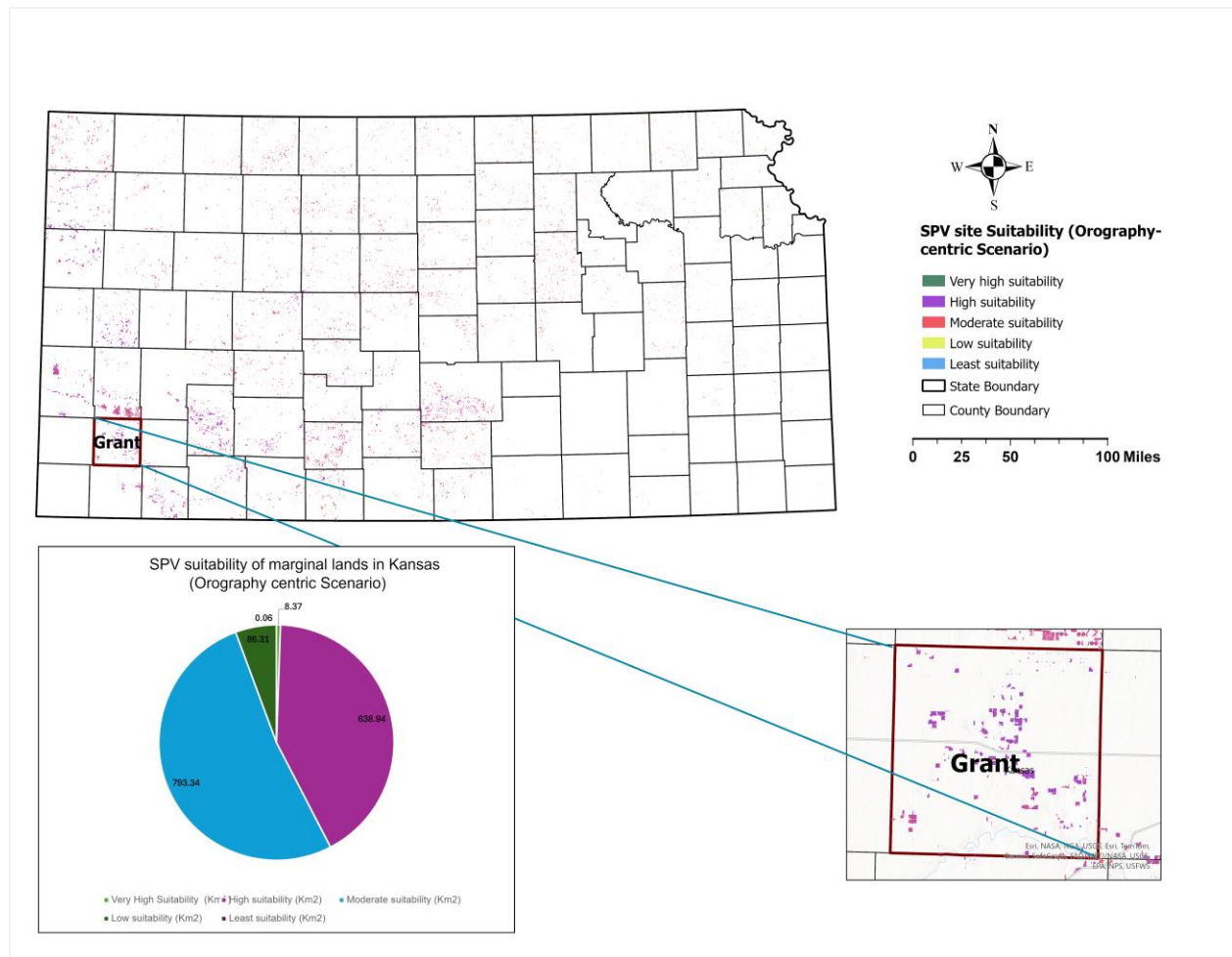


Figure 3.16: Sensitivity analysis: Orography-centric scenario

The base model provides a well-distributed range of suitability areas, with 50.18% of the area rated as 'High' suitability and 47.72% as 'Moderate' suitability. Moreover, the base model demonstrates stability and consistency across different scenarios. These findings demonstrate the reliability of the proposed model (base/reference) and present the optimal location for SPV sites in marginal lands of Kansas.

3.4.6 Limitation

The research has some limitations that could be addressed in future studies within this research area. While my thesis addresses the “NIMBY” (Not in my Backyard) approach, a comprehensive investigation on community acceptance was unable to be conducted due to the

restricted scope of this research. The concept of community acceptance is an important factor in siting decision. The scope of this research is also restricted by the exclusion of certain economic criteria, for instance, cost of land, solar PV installation costs, and operating expenses.

Additionally, this research is limited to identifying suitable solar photovoltaic sites in Kansas.

Future research opportunities could involve an extended study area, for instance including the Great plain States.

3.4.7 Conclusion

The purpose of this research was to identify suitable sites for micro-grid SPV development on marginal lands across Kansas. I adopted a GIS based multi-criteria decision approach for the site selection process. First, I conducted an extensive literature review to identify important factors influencing the location of on-grid solar photovoltaic power plants. Then, I excluded protected areas, wetlands, forests, and agricultural land cover from the study area to minimize environmental, societal, and economic impacts when adopting green energy like SPVs.

Lastly, I ranked the marginal lands in Kansas from most to least suitable for SPVs. The results of this research can be used to lower the cost of electricity, while installing solar photovoltaics in Kansas by focusing on factors such as solar irradiation, sunshine hours, temperature, slope, aspects, distance from roads, residential areas, and transmission lines.

The AHP analysis identified solar irradiation, sunshine hours, and distance from transmission lines as the three most significant criteria among the eight criteria included in my analysis. The final SPV site suitability map indicates that the best locations for SPV in marginal lands are in the western side of Kansas. Approximately 770 km²/ 0.077 million hectares of total

marginal lands are identified as the most suitable locations (very high suitability and high suitability) for SPV deployment in Kansas.

Since the GIS-based weighted overlay analysis heavily relies on opinions derived from expert surveys, I also conducted an extensive sensitivity analysis to observe how changes in the model outcome occur by adjusting the weights of input criteria. I compared the results of different scenarios in response to changes in the site selection criteria used in this thesis. The location-centric criteria appear to be the most sensitive to changes in criteria values, meaning that any changes in the variables under this category will significantly impact the suitability classes and consequently areas under these classes.

In conclusion, this thesis aims to promote the adoption of solar photovoltaics in the marginal lands of Kansas by identifying suitable locations for SPV projects. Although this thesis is limited to marginal lands for SPV site suitability analysis, it serves to alleviate the existing competition between food production and energy generation. I believe this work will potentially contribute to the renewable energy profile of Kansas and can be adapted for SPV development in other Great Plains states in the US.

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Chapter 4: Conclusion

4.1 Evaluation of Research

Renewable energy resources are leading the energy sector with an aim to meet increasing demand. Solar energy has been deemed as one of the promising green sources of energy due to its infinite and clean nature. To keep pace with the rest of the world, the US is also gradually adopting SPV projects, with specific focus on certain states such as, California, Texas, Florida and so forth. These agglomerations in certain states limit the potential of SPV in other states despite having solar potential in other states as well. While researchers have found that Kansas and other Great Plain states have remarkable prospects for SPV development, currently there are only fifty solar companies operating in Kansas, including manufacturers, installers, and developers (Solar Energy Industries Association) with a limited contribution to the total electricity produced in Kansas. While this limitation brings focus on undertaking additional SPV projects in Kansas, it may pose challenges due to potential conflicts with agricultural land use, as SPV projects have specific land requirements.

Thus, my thesis serves to answer three broad research questions (discussed in chapter 01) that derived from one larger problem, which is identifying the most suitable locations for future SPV projects in Kansas. In my research, I specifically aimed at understanding the suitability of marginal lands for SPV deployment that are underutilized and both environmentally and economically unproductive. I hypothesize that the utilization of marginal land for the deployment of solar photovoltaic systems presents a potentially sustainable alternative that can address three interconnected goals: efficient land utilization, environmental conservation, and economic prosperity.

The second chapter of this thesis quantifies, delineates, and validates marginal lands in Kansas. Depending on the criteria chosen to quantify marginal lands, I found different distributions of marginal lands in Kansas. The distribution of marginal lands in Kansas ranges from 0.000124 million hectares to 6.915 million hectares. Additionally, to assess the accuracy of quantified marginal lands, I have utilized Conservation Reserve Program land cover as a ground truth data source. This validation approach added a new dimension to the existing literature on marginal land assessment. Under this validation approach, a small-scale aggregation geoprocessing method has been adopted to assess the accuracy of marginal lands in Kansas. These Common Land Unit boundaries provide a detailed assessment of available marginal lands in Kansas. The accuracy of identified marginal lands varies with presence of marginal land pixel under a certain threshold. The result shows that as the threshold (required marginal land pixel present within a CLU boundary, i.e., 25%, 50%, and 75%) gets stringent, the accuracy of identified marginal land cover decreases, and vice versa. However, an increasing error rate has been observed with decreasing threshold values. I found the 25% threshold model to provide the most accurate assessment of marginal lands; thus, marginal lands identified under this model have been used as the base for SPV site suitability assessment in Kansas.

The third chapter extensively focuses on identifying suitable SPV site locations on marginal lands of Kansas. Based on chapter two only 1.64% of marginal lands have the potential to be utilized for SPV projects in Kansas. However, not all the marginal land parcels possess the same favorability to deploy a SPV projects. Thus, this research classifies the accurately assessed marginal lands into five categories from least suitable to most suitable based on certain (discusses in chapter 03) selection and restriction criteria. My research has identified solar irradiation, sunshine hour, distance from transmission lines and residential areas, and slopes as

the most significant criteria among the eight site selection criteria adopted. According to my analysis approximately 50% of suitable marginal lands (after eliminating restriction criteria) are very high to highly suitable for SPV deployment in Kansas. The most appropriate area encompasses around 770 square kilometers of marginal lands with the capacity for 27,110 micro-grid solar photovoltaic projects. By identifying most suitable marginal lands for SPV development, my research attempts to achieve three long-term goals, (a) optimizing food-energy nexus; (b) employing underutilized land cover for economic development, and (c) promoting the adoption of solar microgrids to the public.

4.2 Further Direction

By identifying the most suitable marginal land parcels for SPV development in Kansas, this research provides invaluable guidance to the decision makers/planner to site future SPV projects in Kansas. Depending on resource availability and accessibility, future research can develop models to propose the most efficient size of SPVs that can be deployed in these land parcels.

While this research takes locational, climatic, and orographic criteria to assess suitability, inclusion of socio-economic aspects could refine the decision-making process. Under the social criteria, this research could further investigate community and landowners' perception prior to developing SPV projects. The consideration of social factors could provide insights to potential barriers and prospects of SPV development in Kansas.

Additionally, this research is limited to identifying potential suitable locations for SPV projects in Kansas. Thus, future work can include other Great Plain States that are lagging behind in terms of installed SPVs. While meeting the increasing energy demand, identifying

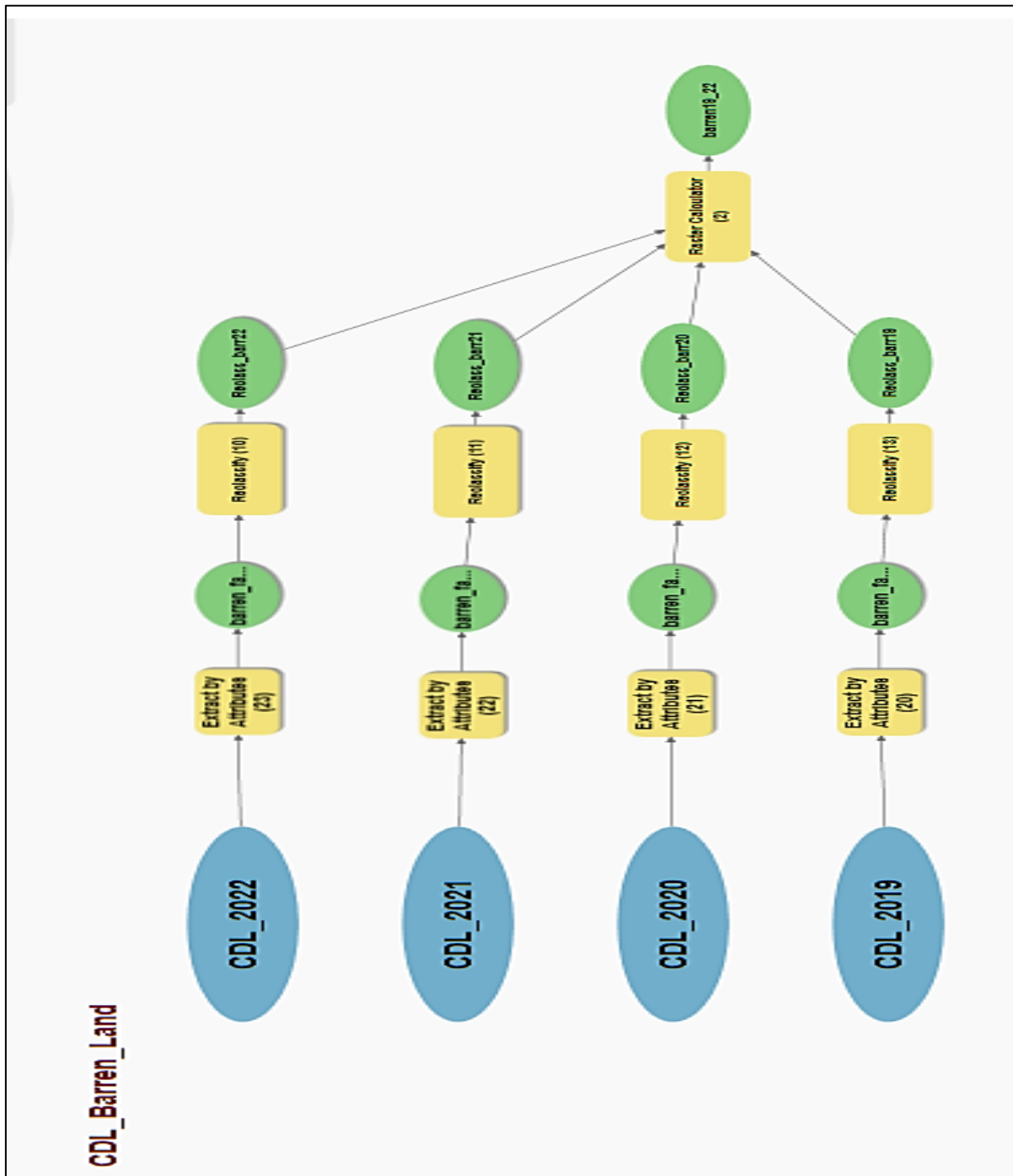
suitable sites in the marginal land of these states will also ensure a balance between food and energy production.

Appendix A: Literature review on marginal land identification

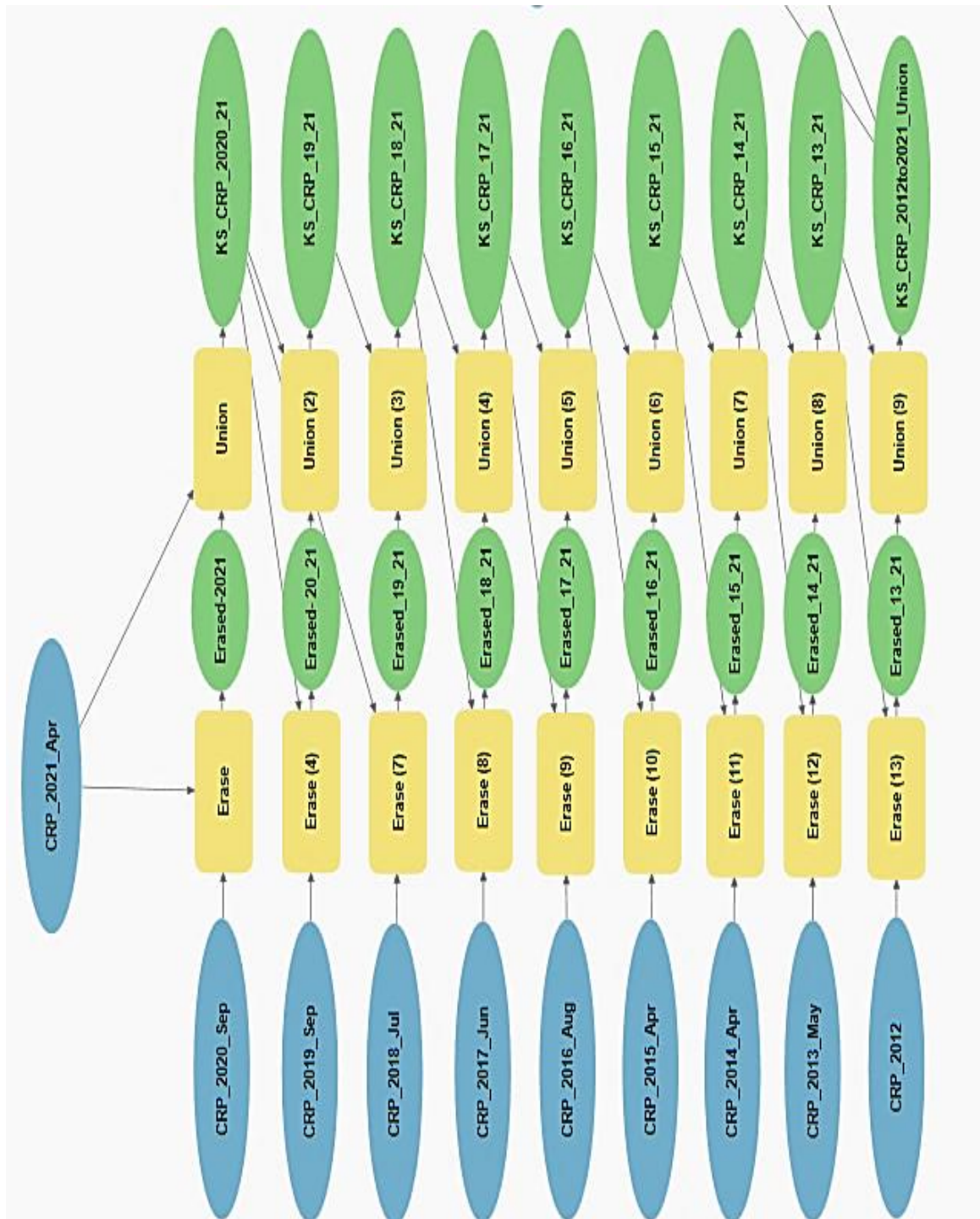
<i>References</i>	<i>Definition of marginal land</i>	<i>Methods</i>	<i>Factors</i>
Khanna et al., 2021	Areas that have limitations in terms of their ability to support conventional agricultural practices for food production.		Soil quality Land productivity Degraded land Abandoned land Idle land Buffer zones Convertible non-crop land Break-even price Land rent Energy crop yield
Emery et al., 2017	1. Moderate ecosystem productivity, based on Cai.et. al., (CMMEP) dataset 2. Abandoned agricultural land, is based on the abandoned agricultural lands assessment by Zumkehr and Campbell, who modeled the spatial distribution of U.S. farmland at 5 min resolution based on historical survey data and satellite mapping from 1850 to 2000. 3. CRP lands 4. selected land cover data sets overlaid with land capability classifications (LCC).	Compared marginal land estimates at national and agro-ecological zone (AEZ) scales using five spatially explicit land cover data sets and four definitions of marginal land	Land cover data
Milbrandt et al., 2014	An integration of: Abandoned lands (Abandoned croplands, Abandoned mine lands), EPA sites include Brownfield, federal/non-federal Superfund, Landfills, Right of ways and Barren lands		Abandoned croplands Abandoned mine lands EPA sites include Brownfield, federal/non-federal Superfund Landfills Right of ways (Roads, Railways and Transmission line) Barren land
Kang et al., 2013	Physically, biologically, and environmentally unproductive land cover	Overlay GIS analysis	Physical Slope, rock fragment, Bedrock depth, flooding, and ponding. Biological Temperature, moisture, soil erosion tolerance rate. Soil depth, sand content, production, cation change

			capacity, salinization, sodicity, Acidity/Alkalinity, Drainage, water Table, Soil layer restriction and others. Environ-ecological: Slope, erosion, wetlands, Nutrient loss, Biodiversity, Resilience, Resistance, Buffer zones or corridors, economically marginal: Breakeven price or yields,
Nijssen et al., 2012	Degraded lands, degraded lands not in use as forest, cropland, pastoral land, or urban (Bioenergy potential)		Soil degradation Perennial energy crop
Cai et al., 2011	Based on agricultural productivity.	Overlay	Soil rating for plant growth Soil productivity land slope soil temperature Humidity index
Wu et al., 2010	Potential marginal land for biofuels		Elevation Soil Meteorological components
Gopalakrishnan et al., 2011	Marginal lands are environmentally degraded land parcels with poor soil health, water pollution and environmentally restricted sites which might also be defined as designated land use type (idle land or CRP or fallow land).		Soil properties: soil erosion, flooding, drainage Orographic: slope Land cover type: idle and fallow cropland, buffer strips along rivers and roadways. Environmentally restricted sites: Brownfields, contaminated surface water resources.

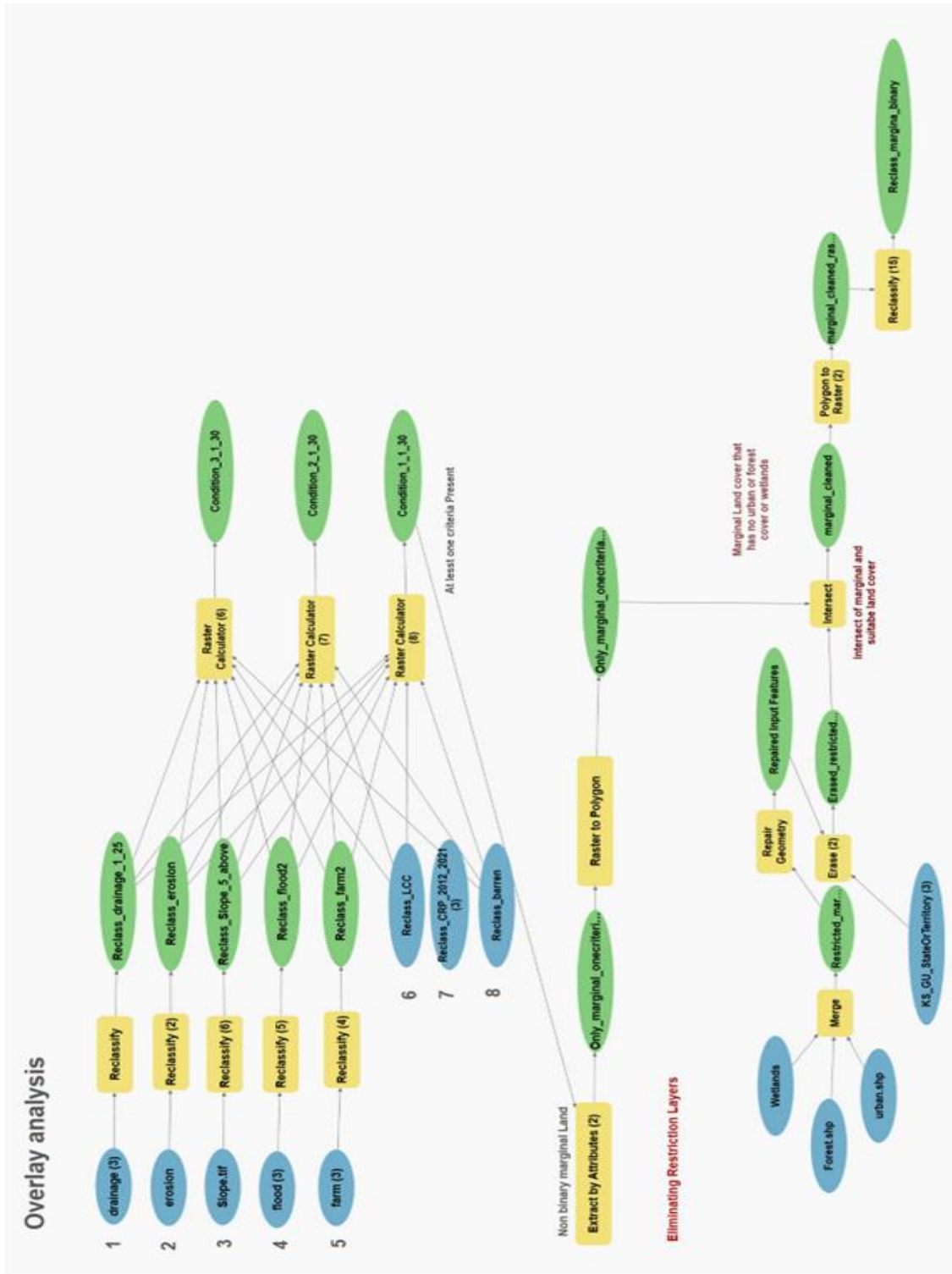
Appendix B: A combination of ArcGIS Pro models used to develop marginal lands in Kansas.



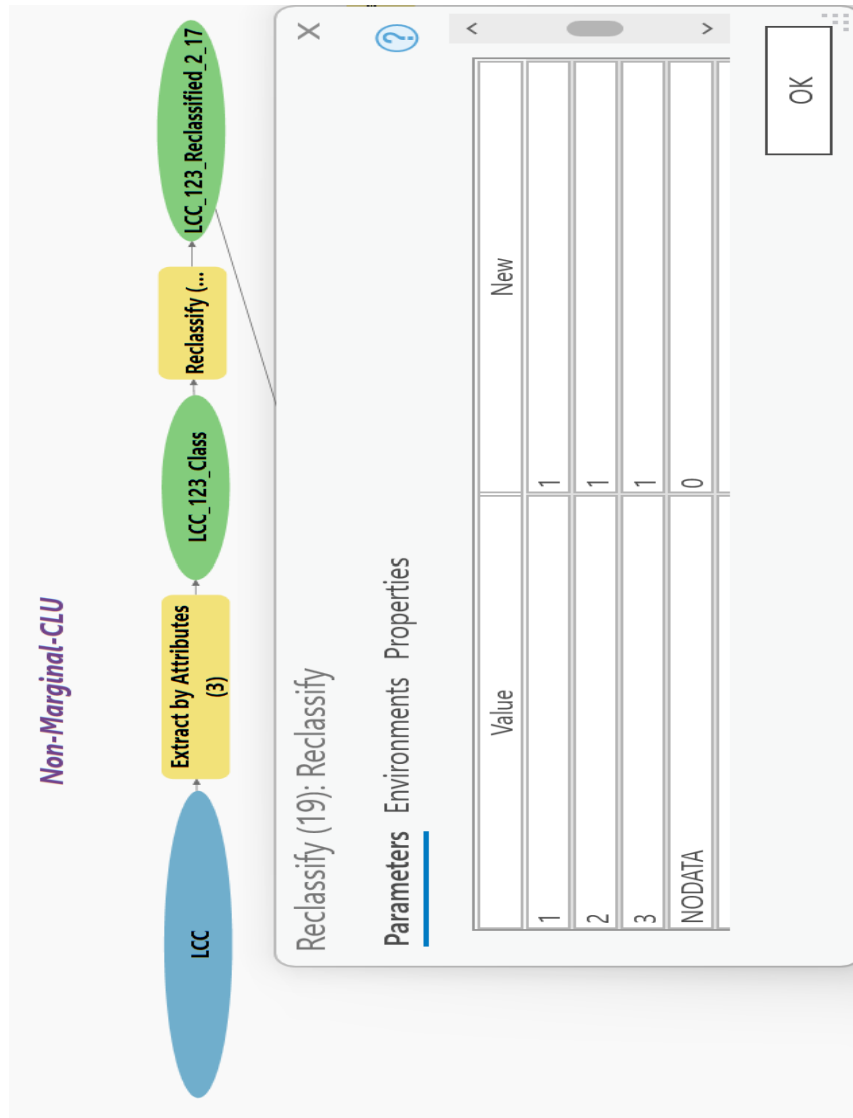
Appendix B.1: Framework to identify Marginal barren land cover.



Appendix B.2: Merging all CRP landcover from 2012 to 2021.



Appendix B.3: Overlay analysis and exclusion of restriction criteria



Appendix B.4: Methodology to identify non-marginal land cover in Kansas

Appendix C: Literature review on solar photovoltaic site selection

No	References	Methods	Location	Criteria
1	Alhammad, A., Sun, Q. C., & Tao, Y. (2022). Optimal Solar Plant Site Identification Using GIS and Remote Sensing: Framework and Case Study. <i>Energies</i> , 15(1), 312.	AHP	Al-Qassim, Kingdom of Saudi Arabia.	Economic criteria: distance from road, powerlines and the slope. Environmental criteria: distances from the protected area, distance from residential areas. Climatic factors: Temperature, precipitation humidity, and sunshine hours
2	Sward, J. A., Nilson, R. S., Katkar, V. V., Stedman, R. C., Kay, D. L., Ifft, J. E., & Zhang, K. M. (2021). Integrating social considerations in multicriteria decision analysis for utility-scale solar photovoltaic siting. <i>Applied energy</i> , 288, 116543.			Techno-economic Factors - Permitting: Climate, Land Preparation, Land Slope, Nearby Renewables, Distance to Existing Infrastructure, Electricity Prices, Elevation, Water Availability, Solar Resource, Land Cover Social Factors – Way of Life: Sense of Place, Visual Impacts, Age, Risk Perceptions, Education, Racial/Ethnic

				Minorities, Cultural Traditions, Regulations, Proximity, Political Identity Common Factors: Jobs, Income, Community Compensation, Public Health, Markets, Geographic Distribution, Values, Competing Land Use"
3	Colak, H. E., Memisoglu, T., & Gercek, Y. (2020). Optimal site selection for solar photovoltaic (PV) power plants using GIS and AHP: A case study of Malatya Province, Turkey. <i>Renewable energy</i> , 149, 565-576.	AHP	Malatya/ Turkey	Solar energy potential Aspect Roads Residential areas Energy transmission lines Fault lines Lakes and dams Transformer centers Natural gas lines Land cover Restricted areas
4	Guaita-Pradas, Inmaculada, et al. "Analyzing territory for the sustainable development of solar photovoltaic power using GIS databases." <i>Environmental monitoring and assessment</i> 191 (2019): 1-17.	Intersect	Valencian Community / Spain	Environmental criteria: (a) Climate: Radiation, temperature and Altitude. (b) Internal soil characteristics: natural fertility, depth, texture, and geology. (c) External soil characteristics

				cs: slope, land cover, and erosion. Social criteria: Landscape impact, Job opportunities and Rural development Economic criteria: (a) Design: solar cells, type of PV panels, and grid connectivity (b) Initial capital cost (c) Discount rates (d) Lifetime of the projects & The electricity retail price which determines the profitability of solar farms
5	Solangi, Y. A., Shah, S. A. A., Zameer, H., Ikram, M., & Saracoglu, B. O. (2019). Assessing the solar PV power project site selection in Pakistan: based on AHP-fuzzy VIKOR approach. Environmental Science and Pollution Research, 26, 30286-30302.	AHP-fuzzy VIKOR approach	Pakistan	Economic (EC) Cost of land (EC1) Infrastructural cost (EC2) Operations and maintenance(EC3) Electricity demand (EC4) Environmental (EN) Flat terrain and without trees site (EN1)

				Wildlife and habitat (EN2) Carbon emissions saving (EN3) Social (SO) Public acceptance (SO1) Employment opportunities (SO2) Effect on local economic development (SO3) Location (LO) Distance to residential areas (LO1) Distance to main roads (LO2) Distance to on-grid transmission lines (LO3) Population density (LO4) Climate (CL) Solar irradiation (CL1) Relative humidity (CL2) Annual air temperature (CL3) Orography (OR) Elevation (OR1) Slope (OR2) Aspect (OR3)
6	Koc, A., Turk, S., & Şahin, G. (2019). Multi-criteria of wind-solar site selection problem using a GIS-AHP-based approach with an application in Igdir Province/Turkey. Environmental Science and Pollution Research, 26, 32298-32310.	AHP	Igdir/Turkey	Elevation case Land cover Aspect Inclination Geological rock type Solar irradiance Temperature Transmission line

7	Jung, J., Han, S., & Kim, B. (2019). Digital numerical map-oriented estimation of solar energy potential for site selection of photovoltaic solar panels on national highway slopes. <i>Applied Energy</i> , 242, 57-68.	Digital Numeric map using ArcGIS and MATLAB	Gongju/ South Korea	DEM Slope and aspects Solar radiation estimation Shaded-area
8	Shorabeh, S. N., Firozjaei, M. K., Nematollahi, O., Firozjaei, H. K., & Jelokhani-Niaraki, M. (2019). A risk-based multi-criteria spatial decision analysis for solar power plant site selection in different climates: A case study in Iran. <i>Renewable Energy</i> , 143, 958-973	Ordered Weighted Averaging (OWA)	Mazandaran , Kermanshah, Razavi Khorasan, and Yazd in Iran.	DEM and slope Normalized Difference Vegetation Index (NDVI) Land Surface Temperature (LST) Dust maps Fault map Precipitation Road network Sunshine hours Solar radiation Distance from city.
9	Nay, Kathleen D. 2018. <i>Agriculture and Solar Energy Development in Massachusetts: Potential Conflicts and Synergies</i> . Tufts University.	Extract by Mask	Massachusetts	Restricted Parcels, Slope
10	Doljak, D., & Stanojević, G. (2017). Evaluation of natural conditions for site selection of ground-mounted photovoltaic power plants in Serbia. <i>Energy</i> , 127, 291-300.	AHP	Serbia	Global solar radiation [kWh/m ² /year]" Duration of sunshine [h] Air temperature [degrees C] Relative humidity [%] Slope [Degrees] Aspect NDVI
11	Anwarzai, M. A., & Nagasaka, K. (2017).	WLC	Afghanistan	Exclusion criteria:

	Utility-scale implementable potential of wind and solar energies for Afghanistan using GIS multi-criteria decision analysis. <i>Renewable and Sustainable Energy Reviews</i>, 71, 150-160.			protected areas and lakes, lands beyond 10 km road access, sand dunes and permanent snow areas, marshland (permanent and seasonal), irrigated land (intermittent and intensive), natural forest (closed and opened), degenerate forest or high shrubs areas, fruit trees, gardens, vineyards, pistachio forest,
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				moreover, settlement or urban areas. Suitable areas: (a) Selection by attributes: Resources, Terrain and slope, Land use. (b) Selection by location: Airport, settlements not within 2000m, rural areas not within 500m single dwellings, rivers, roads
12	Sabo, M. L., Mariun, N., Hizam, H., Radzi, M. A. M., & Zakaria, A. (2017). Spatial matching of large-scale grid-connected photovoltaic power generation with utility demand in Peninsular Malaysia. <i>Applied Energy</i> , 191, 663-688.	Generation-demand	Malaysia	Distance from roads, distance from grid/transmission lines, slope, elevation, and land use. Solar radiation is not considered.
13	Lee, A. H., Kang, H. Y., & Liou, Y. J. (2017). A hybrid multiple-criteria decision-making approach for photovoltaic solar plant location	Interpretive Structural Modeling (ISM), Analytic Network Process (ANP), VIKOR((VlseKriteriju mska Optimizacija I Kompromisno Resenje	Taiwan.	Costs: Land cost, panel cost, maintenance cost, infrastructure cost. Biological: Land utilization, population density.

	selection. <i>Sustainability</i> , 9(2), 184.			Physical environment: Soil quality, weather. Economic: Agricultural impact, future capacity expansion.
14	Sindhu, S., Nehra, V., & Luthra, S. (2017). Investigation of feasibility study of solar farms deployment using hybrid AHP-TOPSIS analysis: Case study of India. <i>Renewable and Sustainable Energy Reviews</i> , 73, 496-511.	AHP-Fuzzy TOPSIS	India	Social aspects: Public acceptance, distance from residential area, effect on economic progress, effect on agriculture, employment and tourism. Technical aspects: solar radiation data, manpower, climate. Economic aspects: Infrastructure cost, Road and rail ,transmission grid. Environmental aspects: Visual impact, wild life and endangered species, noise impact, harmful toxin emission. Political aspects: State government policies, regulatory boundaries, land acquisition, resettlement and rehabilitation.

15	Zoghi, M., Ehsani, A. H., Sadat, M., javad Amiri, M., & Karimi, S. (2017). Optimization solar site selection by fuzzy logic model and weighted linear combination method in arid and semi-arid region: A case study Isfahan-IRAN. <i>Renewable and Sustainable Energy Reviews</i> , 68, 986-996.	AHP-Fuzzy-WLC	Isfahan, Iran	Environmental : Land use, protected area, wildlife and water reserve. Geomorphological: Elevation, slope, aspects. Location: Distance to city, power line, transportation. Climatic: Sunny hours, cloudy days, dusty days, solar radiation, rainy/snowy days, humidity.
16	Noorollahi, E., Fadai, D., Akbarpour Shirazi, M., & Ghodsipour, S. H. (2016). Land suitability analysis for solar farms exploitation using GIS and fuzzy analytic hierarchy process (FAHP)—a case study of Iran. <i>Energies</i> , 9(8), 643.	FAHP	Iran	Climatology: Solar radiation, avg. annual rainfall. Environmental: Elevation, slope, landuse. Location: Distance to residential area, power line, transportation. Meteorological: Avg. annual cloudy days, avg. annual dusty days, avg. annual humidity.
17	Gherboudj, I., & Ghedira, H. (2016). Assessment of solar energy potential over the United Arab Emirates using remote sensing and weather forecast data. <i>Renewable and Sustainable Energy Reviews</i> , 55, 1210-1224.	GIS-Join	United Arab Emirates	Solar irradiation, weather components as aerosol thickness, humidity, air temperature, land use.
18	Merrouni, A. A., Mezrhab, A., & Mezrhab, A. (2016). PV sites suitability analysis in the Eastern region of	GIS-Overlay	East of Morocco	Land exclusion criteria: Infrastructue: Roads, power grids, railway, cities.

	Morocco. <i>Sustainable Energy Technologies and Assessments</i> , 18, 6-15.			Vegetation: forest, protected areas, reforestation. Hydrology: Dams, permanent and non-permanent waterways. Terrain: Slopes.
19	Castillo, C. P., e Silva, F. B., & Lavalle, C. (2016). An assessment of the regional potential for solar power generation in EU-28. <i>Energy policy</i> , 88, 86-99.	WLC	EU-28	Constraints: Protected and sensitive natural areas, built-up areas, wetlands, water bodies and forest Suitability factors: Solar radiation, topographic parameters (slope, aspect, elevation), Population potentially affected, proximity to roads and electricity grid
20	Wang, S., Zhang, L., Fu, D., Lu, X., Wu, T., & Tong, Q. (2016). Selecting photovoltaic generation sites in Tibet using remote sensing and geographic analysis. <i>Solar Energy</i> , 133, 85-93.	GIS-Overlay	Tibet, China	Solar energy, slope, land cover.
21	Watson, J. J., & Hudson, M. D. (2015). Regional Scale wind farm and solar farm suitability assessment using GIS-assisted multi-criteria evaluation. <i>Landscape and urban planning</i> , 138, 20-31.	AHP	South, United Kingdom	Agricultural land classification Historically important areas Landscape designations Residential areas Wildlife designations

				Aspect (solar only) Slope (degrees)
22	El-Azab, R., & Amin, A. (2015). Optimal solar plant site selection. SoutheastCon 2015, 1-6.	Transmitted Energy	MENA	Daily global and direct sun radiation.
23	Borgogno Mondino, E., Fabrizio, E., & Chiabrando, R. (2015). Site selection of large ground-mounted photovoltaic plants: a GIS decision support system and an application to Italy. <i>International Journal of Green Energy</i> , 12(5), 515-525.	ANN	Italy	Solar radiation, temperature, rain height, land cover, restricted areas, protected areas, land use capacity.
24	Calvert, K., & Mabee, W. (2015). More solar farms or more bioenergy crops? Mapping and assessing potential land-use conflicts among renewable energy technologies in eastern Ontario, Canada. <i>Applied Geography</i> , 56, 209-221.	GIS-Overlay	Ontario, Canada	Exclusion areas based on ecological and cultural value
25	Tahri, M., Hakdaoui, M., & Maanan, M. (2015). The evaluation of solar farm locations applying Geographic Information System and Multi-Criteria Decision-Making methods: Case study in southern Morocco. <i>Renewable and sustainable energy reviews</i> , 51, 1354-1362.			Climate: Solar radiation, temperature. Orography: Slope, slope orientation Location: Distance to road, distance to urban area. Land use: Land use.
26	Brewer, J., Ames, D. P., Solan, D., Lee, R., & Carlisle, J. (2015). Using GIS analytics and social preference data to evaluate utility-scale	WLC PV	Southwest, USA	Slope, irradiance, powerlines, rivers, and roads.

	solar power site suitability. <i>Renewable energy</i> , 81, 825-836.			
27	Yunna, W., & Geng, S. (2014). Multi-criteria decision making on selection of solar–wind hybrid power station location: A case of China. <i>Energy Conversion and Management</i> , 81, 527-533.	AHP	China	Grid-connection Solar energy resource Cost Benefit Social risk Environmental protection The adverse impact on the environment and society
28	Jun, D., Tian-Tian, F., Yi-Sheng, Y., & Yu, M. (2014). Macro-site selection of wind/solar hybrid power station based on ELECTRE-II. <i>Renewable and Sustainable Energy Reviews</i> , 35, 194-204.	ELECTRE-II	China	Natural resources: Power density, wind direction, speed, turbulence intensity, effective wind hours, solar radiation, sunshine hours, sunshine days, solar energy variation characteristics. Traffic condition: Traffic convenience degree, means of transportation, and traffic line length. Economic: Total investment, construction interest, project payback period, operation and maintenance costs, return on investment, investment profit rate.

				Environment factors: Pneumatic, noise, light pollution, energy savings, pollution reduction. Social factor: residents attitude. Distance to load center. Geographical condition: Geological/topographic, land use Technical: rated power, cut-in/out wind speed, wake loss effect, Equipment producing area, energy conversion efficiency.
29	Mahtta, R., Joshi, P. K., & Jindal, A. K. (2014). Solar power potential mapping in India using remote sensing inputs and environmental parameters. <i>Renewable energy</i> , 71, 255-262.	GIS-Solar irradiation	India	Environmental: solar irradiation, land availability Transmission grid accessibility. Social: social acceptability, demand for electricity, effect on progress of surrounding region. Risk: political risk, economic risk, time delay risk, environmental risk.
30	Chen, C. R., Huang, C. C., & Tsuei, H. J. (2014). A hybrid MCDM model for improving GIS-based solar farms site	DEMATEL—DANP	China	Environment: Agrological capacity. Orography: Slope, orientation, area.

	selection. <i>International Journal of Photoenergy</i> , 2014.			Location: Distance to road, power lines, villages, substations. Climatology: Solar radiation, avg temperature.
31	Chakraborty, S., Sadhu, P. K., & Nitai, P. A. L. (2014). New location selection criterions for solar PV power plant. <i>International Journal of Renewable Energy Research</i> , 4(4), 1020-1030.	NASA-Solar irradiation	India	Monthly average global solar irradiation.
32	Yun-na, W., Yi-sheng, Y., Tian-tian, F., Li-na, K., Wei, L., & Luo-jie, F. (2013). Macro-site selection of wind/solar hybrid power station based on Ideal Matter-Element Model. <i>International Journal of Electrical Power & Energy Systems</i> , 50, 76-84.	AHP	China	Natural resources: Power density, wind direction, speed, turbulence intensity, effective wind hours, solar radiation, sunshine hours, sunshine days, solar energy variation characteristics. Traffic condition: Traffic convenience degree, means of transportation, and traffic line length. Economic: Total investment, construction interest, project payback period, operation and maintenance costs, return on investment, investment profit rate.

				Environment factors: Pneumatic, noise, light pollution, energy savings, pollution reduction. Social factor: residents attitude. Distance to load center. Geographical condition: Geological/topographic, land use Technical: rated power, cut-in/out wind speed, wake loss effect, Equipment producing area, energy conversion efficiency.
33	Uyan, M. (2013). GIS-based solar farms site selection using analytic hierarchy process (AHP) in Karapinar region, Konya/Turkey. Renewable and Sustainable Energy Reviews, 28, 11-17.	AHP	Konya, Turkey	Distance from Residential areas (m) Road Networks (m) Water bodies Protected areas Land use Slope (%) Distance to Transmission Lines (m)
34	Sánchez-Lozano, J. M., Teruel-Solano, J., Soto-Elvira, P. L., & García-Cascales, M. S. (2013). Geographical Information Systems (GIS) and Multi-Criteria Decision Making (MCDM) methods for	AHP—TOPSIS	Cartagena, Spain	Agrological Capacity Slope Orientation Area Distance to main roads Distance to power lines

	the evaluation of solar farms locations: Case study in south-eastern Spain. <i>Renewable and sustainable energy reviews</i> , 24, 544-556			Distance to villages Distance to substations Solar irradiation potential Average temperature
35	Sun, Y. W., Hof, A., Wang, R., Liu, J., Lin, Y. J., & Yang, D. W. (2013). GIS-based approach for potential analysis of solar PV generation at the regional scale: A case study of Fujian Province. <i>Energy Policy</i> , 58, 248-259.	Geospatial supply	Fujian, China	Geographical: Land cover and DEM. Technical: Total electricity production. Economic: Production cost, payback period, net present value. Environmental: CO2 mitigation.
36	Effat, H. A. (2013). Selection of potential sites for solar energy farms in Ismailia Governorate, Egypt using SRTM and multicriteria analysis. <i>International Journal of Advanced Remote Sensing and GIS</i> , 2(1), 205-220.	AHP	Ismailia, Egypt	Solar radiation, aspects, built-up areas, cultivated land, proximity to power lines, main roads and cuties.
37	Aydin, N. Y., Kentel, E., & Duzgun, H. S. (2013). GIS-based site selection methodology for hybrid renewable energy systems: A case study from western Turkey. <i>Energy conversion and management</i> , 70, 90-106.	Fuzzy OWA	West, Turkey	Environmental: Must protect, natural reserves, agricultural areas, lakes and wetlands, coastline/rivers. Economic: Slope, solar energy proximity to transmission lines, Acceptable proximity to urban areas.
38	Besarati, S. M., Padilla, R. V., Goswami, D. Y., & Stefanakos, E. (2013).	RETScreen-Solar	Iran	Solar radiation

	The potential of harnessing solar radiation in Iran: Generating solar maps and viability study of PV power plants. <i>Renewable energy</i> , 53, 193-199.			
39	Rumbayan, M., Abudureyimu, A., & Nagasaka, K. (2012). Mapping of solar energy potential in Indonesia using artificial neural network and geographical information system. <i>Renewable and Sustainable Energy Reviews</i> , 16(3), 1437-1449.	ANN	Indonesia	Solar irradiation,.
40	Charabi, Y., & Gastli, A. (2011). PV site suitability analysis using GIS-based spatial fuzzy multi-criteria evaluation. <i>Renewable Energy</i> , 36(9), 2554-2561.	AHP-Fuzzy OWA	Oman	Technical: Solar Radiation, land accessibility, Land use. Economical: Grid proximity, slope, load poles. Environmental: Sensitive areas, hydrographic line, sand/dust risk.
41	Jain, A., Mehta, R., & Mittal, S. K. (2011). Modeling impact of solar radiation on site selection for solar PV power plants in India. <i>International Journal of Green Energy</i> , 8(4), 486-498.	Simulation scenarios	India	Weather: Temperature and humidity. Finance: Capital cost, loan term, duration if tariff, tariff rate, interest rate, capacity utilization factor, debt to equity ratio.
42	Arnette, A. N., & Zobel, C. W. (2011). Spatial analysis of renewable energy potential in the greater southern Appalachian mountains. <i>Renewable Energy</i> , 36(11), 2785-2798.	IS-Multiply	Appalachian Mountains, United States	Solar insolation, slope, aspects, LULC, restrictions (Protected area).
43	Janke, J. R. (2010). Multicriteria GIS modeling of wind and solar farms in Colorado. <i>Renewable Energy</i> , 35(10), 2228-2234.	WLC	Colorado, USA	Wind Potential Solar Potential landcover population density federal lands Distance to Roads Distance to transmission Lines"

				Distance to Cities
44	Boran, F. E., Menlik, T., & Boran, K. U. R. T. U. L. U. Ş. (2010). Multi-criteria axiomatic design approach to evaluate sites for grid-connected photovoltaic power plants: A case study in Turkey. <i>Energy Sources, Part B: Economics, Planning, and Policy</i> , 5(3), 290-300.	Axiomatic design	Turkey	Sun hour (h), solar radiation(kW/m2), Mean temperature, topography.
45	Belmonte, S., Núñez, V., Viramonte, J. G., & Franco, J. (2009). Potential renewable energy resources of the Lerma Valley, Salta, Argentina for its strategic territorial planning. <i>Renewable and Sustainable Energy Reviews</i> , 13(6-7), 1475-1484.	GIS-Solar irradiation	Salta, Argentina	Daily clear day total radiation
46	Martins, F. R., Pereira, E. B., & Abreu, S. L. (2007). Satellite-derived solar resource maps for Brazil under SWERA project. <i>Solar Energy</i> , 81(4), 517-528.	GIS-Solar irradiation	Brazil	Solar energy.

Appendix D: Expert Opinion Questionnaire

Optimizing Site Selection for Solar PV Panel using AHP in Marginal Kansas

Start of Block: Help regarding solar photovoltaic (SPV) site selection expert opinion survey

Dear Experts,

My name is Mobashsira Tasnim, and I am a graduate student in the Geography and Geospatial Science Department at Kansas State University. I am currently working as a research assistant under the guidance of Dr. Jason Bergtold and Dr. Marcellus Caldas. Our team is working on a project to optimize site selection for solar photovoltaic (SPV) installation in rural Kansas and the Great Plains, especially on marginal agricultural land.

Our research aims to identify criteria for SPV site selection and rank them based on their comparative significance. To prioritize the various criteria that influence the selection of SPV

sites, our team has adopted a goal-based approach known as analytical hierarchy process (AHP). This approach requires expert input in helping to identify the importance of and tradeoffs between different siting criteria. As you have extensive background knowledge in solar energy, we believe that your insights could significantly enhance the accuracy and relevance of our findings.

We would appreciate it if you could complete a survey asking you to compare different site selection criteria based on your professional and expert judgment. The survey should take approximately 5-7 minutes to complete and ask you for some basic information about your expertise and a series of questions comparing different site selection criteria.

Your participation is entirely voluntary and you have the right to withdraw participation from the research at any time. The survey may not provide any direct benefit to you, but indirect benefits as a result of your participation may include helping to guide solar siting outreach and policy guidance. For concerns or to gain further information about your rights as a participant, you may contact the University Research Compliance Office at 785-532-3224 or fax at 785-532-3278 or by email at: comply@k-state.edu.

The input and data collected will be kept strictly confidential. None of the information you provide will be made identifiable or directly connected or associated with names, addresses, and/or personal identifiers. Instead, a project-specific identifier will be associated with your survey responses, which is not linked back to your name and personal information. Thus, all data will be processed using these identifiers to protect the individual integrity of the data. Only authorized persons working on the project at Kansas State University will have access to the data. In addition, only summaries and general findings from the data will be published or presented to the public, so that no statistics that could potentially identify an individual will be reported. The information that will be collected as part of this research could be used for future research studies by the project investigators or distributed to other approved investigators for future research without additional informed consent after all identifiers have been removed.

Your input is extremely valuable, and we look forward to your participation in this project. The findings from the survey will be available to you if requested. If you have any questions, please do not hesitate to contact me at mtasnim@ksu.edu or by phone at 785-317-9719. You can also contact my advisor, Dr. Marcellus Caldas, at caldasma@k-state.edu. Thank you for your time and consideration.

Best regards,
Mobashsira Tasnim

Please indicate if you CONSENT to participating in the study by taking this survey

☐ I DO consent to participating in this study (1)

☐ I DO NOT consent to participating in this study (2)

Skip To: End of Survey If Please indicate if you CONSENT to participating in the study by taking this survey = I DO NOT consent to participating in this study

End of Block: Help regarding solar photovoltaic (SPV) site selection expert opinion survey

Start of Block: Introduction

This questionnaire employs the Saaty's Analytic Hierarchy Process (AHP) scale, ranging from 1 to 9, for assessing the relative importance of pairs of criteria in the context of SPV site selection. Each criterion is evaluated against others through pairwise comparisons to establish their impact. The list of criteria is provided below;

Table 01: Selection Criteria

Code	Criteria
C1	Solar irradiance
C2	Proximity to transmission lines
C3	Distance from residential areas
C4	Proximity to transportation routes
C5	Temperature
C6	Sunshine hour
C7	Slope
C8	Aspects

The comparison scale is detailed in Table 02. The extent to which one criterion is preferred over another is indicated on the left and right sides for Criterion 1 and Criterion 2, respectively. If you deem the factor at the top to be significantly more important than the one at the bottom, please mark the column with the number 7 on the left side. Conversely, if the bottom factor is considered more important than the top, mark the column with the number 7 on the right side. However, if you believe that the two criteria are of equal importance, you should select the center option, indicating 'equal' (1).

Table 02: Pairwise comparison scale (Satty, 1980)

Scale	Description
1	Equally important
3	Moderately more important
5	Strongly more important
7	Very strongly more important

9	Extremely more important
2, 4, 6, 8	Intermediate values (for compromises)

We kindly ask you to apply this methodology to evaluate various factors systematically. Your participation is crucial to this study, and we thank you for your cooperation and effort in completing this survey.

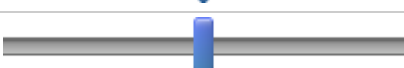
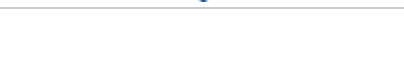
End of Block: Introduction

Start of Block: Default Question Block

Pairwise comparison scale of different conditioning factors

(Example: For the first pair, if you consider solar irradiance (numerator) to be more important, drag your slider to the left. However, if you find sunshine duration to be more significant, drag the slider to the right).

9	7 (Very	5	3	1	3	5	7 (Very	9
(Extremely	strongly	(Strongly	(Slightly	(Equal)	(Slightly	(Strongly	strongly	(Extremely
Important)	important)	important)	important)		important)	important)	important)	Important)
				1	2	3	4	6
							7	8
								9
								10

Solar irradiance/Sunshine hour ()	
Solar irradiance/Distance from transmission lines ()	
Solar irradiance/Proximity to transportation routes ()	
Solar irradiance/Distance from residential areas ()	
Solar irradiance/Temperature ()	
Solar irradiance/Slope ()	
Solar irradiance/Aspects ()	
Proximity to transmission lines/ Distance from residential areas ()	
Proximity to transmission lines/ Proximity to transportation routes ()	
Proximity to transmission lines/ sunshine hour ()	
Proximity to transmission lines/ slope ()	
Proximity to transmission lines/ aspects ()	
Proximity to transmission lines/ Temperature ()	
Distance from residential areas/ Proximity to transportation routes ()	
Distance from residential areas/ Sunshine hour ()	
Distance from residential areas/ Slope ()	
Distance from residential areas/Aspects ()	
Proximity to transportation routes/ Aspects ()	
Proximity to transportation routes/ Temperature ()	
Proximity to transportation routes/ Slope ()	
Proximity to transportation routes/ Sunshine hour ()	
Temperature/ Sunshine hour ()	

Temperature/Slope ()	
Temperature/ Aspects ()	
Sunshine hour/Slope ()	
Sunshine hour/Aspect ()	
Slope/ Aspect ()	
Distance from residential areas/ Temperature ()	

Q2 Current Role

Q3 Area of Expertise

Q4 Years of Experience

- ☐ ≤5 (1)
- ☐ 6-9 (2)
- ☐ 10-14 (3)
- ☐ ≥ 15 (4)

End of Block: Default Question Block