MODELING OPEN SPACE ACQUISITION IN BOULDER, COLORADO

by

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DEDICATION

I dedicate this thesis to my five children for sharing my time and attention with years of academia. My wish for each of them is to succeed in their personal endeavors and never consider themselves too old or too young to accomplish their goals. Thank you to my family for their constant support and encouragement, their intellectually and environmentally conscious conversations, and for reminding me what is most important in life.

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LIST OF ABBREVIATIONS

AAG	Association of American Geographers
BOCO	Boulder County
BVCP	Boulder Valley Comprehensive Plan
CE	Conservation Easement
CNHP	Colorado Natural Heritage Program
COGCC	Colorado Oil and Gas Conservation Commission
COB	City of Boulder
COMAP	Colorado Ownership Management and Protection
CPW	Colorado Parks and Wildlife
FEMA	Federal Emergency Management Agency
GIS	Geographic Information Science
GIST	Geographic Information Science and Technology
HCA	Habitat Conservation Area
MOSA	Modeling Open Space Acquisition
NDIS	Natural Diversity Information Source
NDVI	Normalize Difference Vegetation Index
NHD	National Hydrographic Dataset
OSMP	Open Space and Mountain Park
USDA	United States Department of Agriculture
USGS	United States Geological Survey

ABSTRACT

Purchasing land for open space use is crucial for municipalities that are concerned with conserving land and mitigating urban sprawl. Land-use modeling measures the ecological value of a parcel, with budget constraints in mind, as an ecological vs. economic tradeoff. This thesis develops a land-use modeling system termed Modeling Open Space Acquisition (MOSA) that quantifies the ecological value of land targeted for open space acquisition. MOSA is designed as a decision support tool for local policymakers to identify ecologically rich parcels that can be targeted by using a multi-criteria model. Each parcel in the study area (Boulder, Colorado) is ranked by weighted criteria generated from a variety of data sources. The weighted criteria include wildlife habitat, agricultural lands, historical sites, recreation corridors, vegetation biodiversity, riparian wetlands, parcel proximity, and parcel size. While other weighted land-use models primarily use vector data (i.e., shapes with defined boundaries), the MOSA approach developed here uses raster data. Each cell in the raster dataset represents 150 square feet in the study area. In a parcel, the numerical average of the parcel's cell values represents its ecological contribution, which can be used to determine highly natural resourced land and to provide supplemental evidence to quantifying, targeting, and prioritizing parcel acquisition for preservation. Governing agencies can benefit from land-use modeling like MOSA where parcel acquisition is evaluated from a scientific classification of natural resource capital over a parcel's economic value alone.

CHAPTER ONE: INTRODUCTION

Open space can be defined as land that is unobstructed by development and accessible to the public. Ecological contributions from natural resources add to the benefits of open space parcel purchase. Land resource quality can be quantified by overlaying ecological spatial data into a multiple criteria Geographic Information System (GIS) environment, where each data input is assigned a level of priority decided upon by city planners. Ideally, the parcels with greater than average ecological value can help city planners to justify their acquisition for open space.

Protecting land for open space is increasingly critical for environmental health; it connects communities and mitigates urban sprawl. The numerous ways of prioritizing, planning, and protecting land's intrinsic beauty vary between political, economic, and ecological contexts. Whether a parcel contains rare flora or fauna, produces agriculture, or serves as a contiguous byway for urban connectivity, the land can be valued both monetarily and ecologically. This dichotomy raises traditional debates between open space preservation and the monetary expenditure required to acquire it. Ecologists may argue that economists are "narrow and anthropocentric" when viewing the importance of ecological systems because they tend to focus on the immediate impacts rather than the long term and indirect implications to ecosystem integrity (Bockstael et al. 1995).

Economists are often impatient with ecologists for disregarding human preferences in land-use and urban development. Decision makers analyze the benefits of recreational opportunity, open space contiguity, and habitat conservation, often under the political pressures of taxpaying citizens and interest groups. Other concerns of open space acquisition include budget constraints, justification of purchase, management, and public scrutiny. Unfortunately, many decision makers rank economic value of land more heavily than ecological value, which can lead to purchasing parcels with few contributions toward environmental wellbeing. Land-use modeling enables public agencies to objectively rank a criterion that classifies land by its natural capital. This thesis develops a GIS based parcel prioritization system termed Modeling Open Space Acquisition (MOSA) to classify land by its ecological value prior to parcel purchase.

1.1 Motivation of Research: Why Open Space Matters

Open space provides ecological services for human health. The vast benefits that parks and natural areas provide are complemented by wetlands, forests, and wildlife habitat, where open space provide aesthetic benefits in growing metropolitan areas and may offer relief from congestion and other negative effects of land development (McConnell and Walls 2005). When a community embraces the value of open space and connects with its environment, it can lead to the paradigm shift described by Aldo Leopold when he writes, “We abuse land because we see it as a commodity belonging to us. When we see land as a community to which we belong, we may begin to use it with love and respect” (Leopold 1949, 8). When open space is selected carefully and managed appropriately its eco-services contribute greatly to a community’s quality of life. The community that embraces the cost benefits of public land is likely more willing to support land acquisition taxation. The financial contributions of future generations are deemed the measurement of a community’s willingness to protect and preserve intrinsic natural land (Bradley 2010).

The United States Department of Interior has long practiced funding the purchase of public lands through tax dollars for habitat conservation. The US National Wildlife Refuge System Improvement Act of 1997 directs the Secretary of the Interior to strategically plan and strive for continued growth toward the benefit of ecosystem conservation (Gergely et al. 2000).

As a result of congressional mandates, conservation lands are devoted to preserving the natural habitat of native vertebrates, macroscopic invertebrates, vegetative communities, agriculture production, and other categories of ecosystems and ecological integrity. Local and federal government rely heavily on taxpaying citizens to support and fund open space acquisition. Recreational use at these public parks through entrance, membership, and commerce fees subsidize the cost of public land management and may increase intrinsic public perception by connecting with nature through personal experience. Citizens who enjoy their surroundings in open space and park recreation are more willing to support land acquisition (Erickson 2006).

1.2 Background: Qualifying Open Space

Land can be qualified by its level of ecological value prior to considering it for open space. Ecological systems provide crucial life supporting interdependence that is beneficial to gross national product and to human health. Recent conservation prioritization efforts claim the ability to synergistically conserve bio-diverse ecosystem services that preserves ecologic functions in nature while contributing to the wellbeing of humanity (Izquierdo 2012). Functioning ecosystems can be classified by their quality of biological habitat and their contribution toward human welfare, both directly and indirectly. For example, this can include preservation of wildlife corridors, protecting wetlands, watersheds, and air quality. It might also include development of advantageous natural environments like recreational hiking and biking trails or city parks and connective greenbelts throughout an urban area. Humans often neglect the value of these ecological services and disagree about preserving them. Ecosystem services are often neglected in commercial market evaluation and policy decision-making when compared with traditional economic and manufactured capital that may compromise the sustainability of mankind (Costanza et al. 1997). Economic, ecologic, and sociologic conditions vary over time in an ecosystem where humans coexist with nature; thus people's attitudes towards open space preservation and their willingness to support it will also vary (Gomez-Pompa et al. 1992).

Prioritizing areas for preservation should be based on clear objectives that state the intent of the open space plan and program. Most communities agree on the benefits of sustainable ecological services as general goals of open space preservation. These benefits include preserving town character and limiting urban sprawl. Protecting natural resources and wildlife habitats to ensure public health and safety are also contributions of open space. Recreational benefits of managed trail systems enhance the visitor's experience through hiking and biking while preserving greenways provide connective byways from the city to the suburbs. Agriculture is another added benefit of maintaining open space for farmers growing locally and organically.

Qualifying open space is one challenging issue in land-use planning. Acquiring real estate for open space is described as a combination of natural resources where the greatest value is in the sum of their individual parts (Miles et al. 1996). Highly creative planning in parcel selection is an effective combination of financial resources and professional skills working synergistically to create land that is economically sound, aesthetically pleasing, and environmentally responsive. There are many considerations of parcel selection: its size, its proximity to other protected land, its recreational benefits, the presence of wetland or critical habitat, and importantly, its price if the owner is willing to sell. Standard real estate appraisal is often based on the market value of nearby properties. Land-use priority can also determine the value of a parcel at a given price when the appraisal may not arrive at market value when one considers the parcel's planned use of development (Friedman 1990). The parcel in close proximity to existing open space land that connects a recreational corridor may be worth the extra expenditure, as opposed to a parcel with fewer assets. Some residents are hesitant to sell at any given value and would require sufficient incentives to sell their land (McDonald et al. 2001). With many issues at hand city planners weigh the cost benefits of open space valuation and often must explain why they choose to purchase one parcel over another (Czech 2001).

1.3 Study Area: Boulder, CO

Boulder, CO offers the unique case study of wilderness that has high intrinsic value to its citizens and is largely managed as public land. Private land is also highly valued, and city planners regulate land use to conserve and protect habitat biodiversity. This thesis develops a local case study of an ideal land conservation model for Boulder, Colorado, located approximately at 40.00 latitude and -105.17 longitude.

Boulder is distinguished by the city being mostly surrounded by public open space, conservation easements, county public land, subdivisions, or privatized agricultural lands worth great value. However, because the city annexation limit has had a no-growth policy since 1967, the land within the study area exhibits the influence of an urban island price bubble, which inherently inflates the cost of open space acquisition (Power and Turvey 2010). Between the years of 1950 and 1970 Boulder experienced massive population and commercial growth at the rate of around 6.0% per year. The citizens quickly passed many growth control ballots in the following years limiting the number of jobs supported within the city limits and how many new dwellings are built. Aggressive open space land purchases and urban control policy have limited population growth in Boulder to nearly 0.5% per year for the past decade. Because of progressive foresight in urban planning, Boulder is one of the first cities in North America to publicly purchase and manage a prime open space landscape.

A growing urban economy allows a significant tax base with which to purchase public land to mitigate urban sprawl. However, such land is often expensive in high demand areas. Citizens within the Boulder community generally pride themselves in supporting ecosystem conservation while sustaining a balanced coexistence with nature. Through self-imposed sales taxation, citizens have voted to support land acquisition, which adds annually to the approved city council budget for land acquisition, restoration, and management. In 1967 Boulder, CO citizens made history by voting 77% in favor of a sales tax specifically to buy and maintain natural lands. This election marked the first time voters in any United States city passed a self-imposed sales tax in support of open space land acquisition for preservation. Previously, in 1959 Boulder's charter was amended to include the "Blue Line," which set the western edge of the city at an elevation, where sewer and water services are unavailable, as an attempt to mitigate development while preserving Boulder's mountain backdrop.

The City of Boulder owns and manages more than 46,000 acres of Open Space and Mountain Parks land in and around Boulder, Colorado. The very first piece of land, 80 acres at the base of Flagstaff Mountain, was purchased by the city in 1898 to be used as one in a series of Chautauqua cultural centers around the country. Since then, the Open Space program has acquired over 400 separate properties. The study area in and around Boulder, CO includes 89,238 acres (Figure 1.1). The study area includes four subsections: Table Mountain, Mountain Parks, Jefferson County Partnership, and the Boulder Valley Comprehensive Plan Accelerated Area (City of Boulder Land Acquisition Report 2013).

The remainder of this thesis is organized as follows: Chapter 2 describes work related to the problem of modeling open space prioritization; Chapter 3 introduces the land-use model (MOSA) created in this thesis then details its methodology; Chapter 4 discusses the MOSA model results and interrogates the sensitivity of the MOSA land-use criterion; and Chapter 5 concludes with future model considerations and closing discussion.

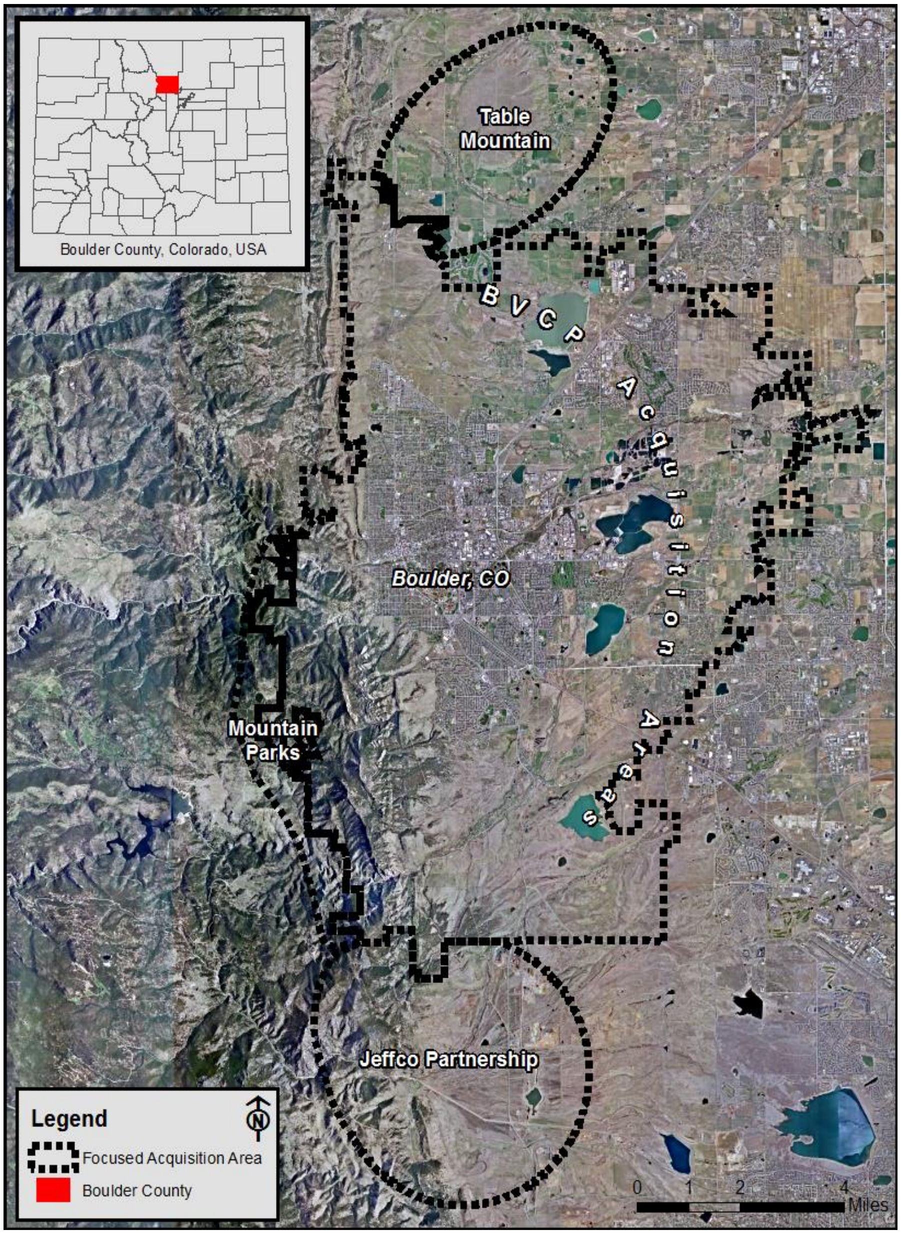


Figure 1.1: Sample Area of Boulder, CO

CHAPTER TWO: RELATED WORK IN MODELING OPEN SPACE PRIORITIZATION

Municipalities like the City of Boulder can benefit from land-use modeling because parcels considered for acquisition can be examined spatially prior to its acquisition. The research of land-use modeling includes multi-criteria decision making land-use modeling using expert based priority ranking with the intent of classifying a parcel's natural values. The model outcome identifies hot spots where land is most ecologically significant, thus providing evidence to prioritize parcels for open space purchase.

Digital GIS data layers in land-use modeling are defined spatially and are collected by reliable sources. Effective land-use models consider digital data representation of specific types of real world phenomena. Ecological models are specific to a particular geographic region and simulate the complex dynamics of a natural ecosystem (Watzhold et al. 2005). Figure 2.1 from the City of Rocky Mount, NC shows sample data inputs in GIS map overlay that can translate different parameters depending on the decision maker's choices.

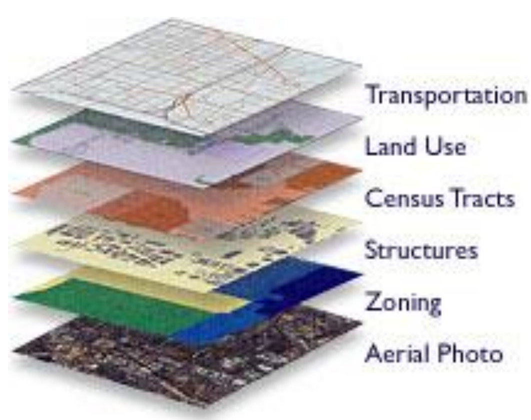


Figure 2.1: An Example of using GIS Data Layers in Criteria Modeling
Graphic Provided by the City of Rocky Mount, NC

Multiple criteria evaluation is the process of ranking a set criteria outlined by an expert(s). Human interaction such as between city planners, city council, and taxpayers' support serves as the "expert" that determines the relative importance of set criteria. Several benefits to multi-criteria decision making are: 1) it accounts for multiple and conflicting criteria, 2) it supports the management of ecosystem services, 3) it models a criteria structure open for discussion, and 4) it offers a process that leads to rational, justifiable, and explainable decisions (Mendoza and Martins 2006).

Additional benefits of multi-criteria modeling is that human experts can interact with planning objectives, both qualitative and quantitative measurements, within an environmental context. The spatial relationships between interacting variables will therefore present recognizable patterns or tendencies of likeliness, thus aiding the recognition of ecological clusters (Lei et al. 2005). Expert opinion based land-use models employ various mixed data sets to represent real-world criterion to determine these spatial patterns in relation to set criterion. The adaptive decisions of a growing city or changing budget constraints are two criteria outside of ecological values that experts could bring to multi-criteria model.

Some challenges with modeling environmental simulation are the purpose that model serves, the operational dynamics within the model, and the extent of model replication, validation, and functionality to ultimately be communicated and shared with others (Crooks, Castle, and Batty 2008). When classifying any ecological criteria for open space acquisition a model should be adaptive with interchangeable data layers, functional with consistent results, replicable for others to adopt, and modifiable to support the interactions of expert opinion that change over time. The MOSA approach built in this thesis is a flexible and functional land-use model because the criteria ranking and inputs can be change as needed within the priority ranking of the weighted sum tool. The model inputs are exploited in the sensitivity analysis to verify and validate how strongly the data are affecting model outcomes.

Accepted methods of criteria ranking and priority modeling include veto threshold, hierarchical structure, and weighting (Rowley et al. 2012). In veto threshold modeling, a minimum performance benchmark is established for each criterion, such as cost or distance parameters. If an alternative does not meet this benchmark with respect to every criterion, it is omitted from the set of feasible options. For example, a parcel that is priced over an acquisition budget is omitted from the dataset.

In hierarchical modeling, set criteria are arranged in order of importance where secondary alternatives are sequentially measured against each other. This includes habitat suitability analysis where the impacts of trail type, size, length, and use through a wildlife corridor are evaluated per overlapping pixel representing the square area within a parcel. For example, the MOSA model primarily uses weighted modeling where each criterion is assigned a numerical value representing either its importance or its trade-off strength under the criterion set by the decision-making expert, including public input, city planning recommendations, and city council approval. Weighting occurs when each of the data layer pixels are multiplied by their derivative of importance and then stacked upon each other and summed. The parcel boundary determines the area per parcel and the pixels within are averaged into a “suitability index” of ecological value. The suitability index is the hierarchical comparison of parcels within the study area.

2.1 Examples of Land-use Prioritization Models

This thesis considers existing land-use prioritization models that use criteria ranking and weighted sum models when identifying lands for preservation. Effective land-use models follow a methodology in which the complexities of ecological, economic, and sociological factors weigh the cost benefit of parcel purchase and preservation (Figure 2.2). The economic and sociological factors are not addressed in this research, but are notably influential upon the overall equilibrium and sustainability of a given ecosystem (Romero 1996).

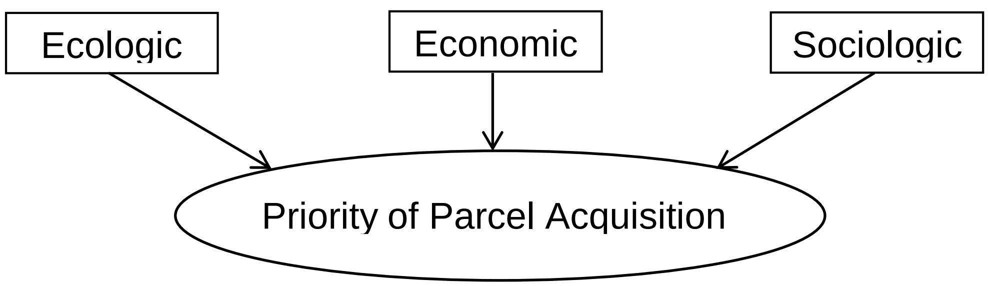


Figure 2.2: Effective Methodologies of Land-Use Modeling

In 2001 the Department of Fisheries and Wildlife and Michigan State University produced a socio-economic-ecological simulation model of land acquisition to expand a national wildlife refuge (Zhang 2012). Each parcel of land in the proposed acquisition area is classified as high priority, medium priority, or low priority based on its evaluated habitat potential for both upland and wetland species. The general structure of the model includes specific objectives of the user and parameterization of ecological, economical, and sociological components. Common land use GIS models referred to as support tools incorporate the related anthropocentric and ecological value of land, its market price, and key indicators of human quality of life when evaluating land-use decisions for open space. Cross-disciplinary collaboration of ecological, economical, and societal effects on human wellbeing through ecosystem-services are beneficial in quantifying the many values of open space preservation (Norman et al. 2010). This land use model is structured to view the ecological impacts separately, allowing decision-makers to evaluate the ecological tradeoff value of land.

The ecological component of the model contains physical information about a parcel's size, location, soil, and land-cover type. The economic element considers the amount of money willing sellers would be compensated for their land at the appraised fair market value, and the monetary incentives above fair market value that would encourage undecided land owners to sell their land. The sociological factors include the attitudes of landowners who choose to sell their land willingly, with incentives, or who are not willing to sell their land at any given amount. The additional variable of land value incorporates the sociological factor of people's willingness to sell their land if given a generous cash incentive. Finding which parcels of land are available for purchase is necessary in knowing how many land parcels are absolutely for sale, how many parcels are possibly for sale, and how many parcels are not for sale (McDonald et al. 2001).

Based on a criteria model of the Flint Creek Watershed-Based Plan (Flint Creek Watershed-Based Plan 2007), input data layers for their model include parcels that intersect Federal Emergency Management Agency (FEMA) 100-year floodplain or wetland, are located within 0.5 miles of any headwater stream, located within 100 feet of a water course or lake, and are adjacent to or includes ecologically significant areas. The Flint Creek land-use model stacks the data inputs in GIS where the digital shape of each parcel polygon is assigned numeric value in map overlay. As the vector data stacks upon each other, the numeric values of the parcels grow additively in potential of land priority. The parcels are classified from very high priority to very low priority depending on the combined numeric score of the GIS model and are grouped according to its applicability toward meeting the project goals. The MOSA model is similar in its criteria ranking structure; but rather uses 150 square meter raster grid overlay in the weighted sum tool where multiple inputs are stacked upon one another producing a final numeric pixel value representing the natural values of a given parcel. The benefit of raster data is calculating zonal statistics per parcel and per sample area where the mean value is classified by resource richness.

In 2006, the town of Stonington, Connecticut adopted a similar model while prioritizing land for open space acquisition (Gibbons 2011). Like the City of Boulder, Stonington's primary goals of open space conservation include protecting wildlife habitats, enhancing biodiversity, maintaining farm land, serving aesthetic purposes, providing recreational opportunities, preserving community character, and increasing contiguity between existing open space parcels. The Conservation Commission established a list of criteria using GIS data layers to evaluate individual parcels of undeveloped land. The GIS mapping allows planners to view the parcels spatially, relative to the town's natural resources and man-made features, such as roads and subdivisions. The Stonington model omits any parcel smaller than thirty-five acres because they deem it insignificant to wildlife. The MOSA land-use model omits subdivision parcels that are already zoned for housing development yet considers every private parcel in the sample area as a potential open space connection.

Another land-use model is discussed in the Wake County Open Space Plan where city planners use GIS to overlay separate layers of information to reveal patterns of interrelated landscape features (Open Space Prioritization Process of Wake County 2006). Once spatial relationships are determined and patterns revealed, decisions can be made and implemented to meet the goals defined by the city planners. The parcel methodology omits private parcels under

50 acres in size and all parcels more than five miles from wetlands. Strategic methodology in land-use planning is important to Wake County where prospective open space and conservation land sellers are competing for limited acquisition funds. This model includes human resource needs like water supply watersheds, recreation water, groundwater recharge areas, and parklands that are weighted by priority. Natural resource needs include endangered species, significant natural heritage areas, vegetative communities, riparian buffers, wetlands, water recharge areas, and floodplains. The data inputs are tested for their interdependency, or their influence upon the model outcome. Each variable is weighted according to planning objectives and parcels are ranked through a matrix of classification. The subjective element to these land-use analyses is the criteria or list of priorities set by the decision-making expert.

CHAPTER THREE: METHODS OF MODELING OPEN SPACE ACQUISITION (MOSA)

This chapter describes the process of building and authoring the Modeling Open Space Acquisition (MOSA) land-use model. MOSA is built on the geo-processing Weighted Sum tool in Esri ArcGIS as a technical, methodical approach that assists in classifying the ecological value of land parcels. By testing the spatial data within the model, highly resourced land is identified and targeted for open space acquisition. MOSA is specifically designed to provide supplemental evidence in determining natural resource contributions of Boulder parcels.

3.1 Source Criteria in MOSA

The City of Boulder is governed by nine publicly elected city council members. Urban planning depends on the professionals appointed by the City council, their priorities, planning strategies, and political pressure placed on them. Every six years the city reviews the acquisition plan of the open space administration. Open Space & Mountain Parks (OSMP) employs environmental scientists, ecologists, and biologists who collect data and manage projects over 46,000 acres of public land. The City of Boulder is the first city in North America to designate their own department for open space preservation (OSMP), aside from Parks & Recreation. OSMP bases its goals and priorities through five Board of Trustees members who discuss current affairs with staff and make recommendations to the Boulder City Council.

The year 2013-2019 acquisition process by OSMP presents a viable opportunity to use multi-criteria decision analysis when planning open space acquisition by systematically applying weighted criteria in a GIS model. The weight of each criterion is mostly decided upon by the City of Boulder open space charter mission. The data layers used in MOSA are collected from public sources and can adequately represent the criteria of the City of Boulder. MOSA was accepted by the Boulder city council as a viable tool in real estate acquisition for OSMP in 2013 (City of Boulder Land Acquisition Report 2013).

Among the criteria for modeling the suitability index (i.e., the ecological richness) of a parcel, property proximity is the most valuable contribution in open space acquisition because the primary goal of the charter is to build connecting corridors of contiguous open space. The riparian areas are second most important because wetlands support a plethora of prime habitats that contribute a wide spectrum of ecological benefits. Open space land around the foothills of Boulder supports vast species of flora and fauna that thrive at that biodiverse ecotone. Three mountainous river systems merge into the western tributary of the Arkansas River: Boulder, South Boulder, and Lefthand Creeks. The land within a mile or so of these river systems is visibly richer in ecological resources. State and federal datasets with moderate details of wildlife corridors are analyzed in MOSA. Recreational benefits from open space include public connections to nature and increase public willingness to support it. When considering trail use, the city council listens intently to public opinion, so recreation is weighted as moderately important. Farms have cultural assets that improve their property value, and agriculture is weighted as increasingly heavy in real estate acquisition because growing locally is a primary goal for the City of Boulder.

3.2 Data Collection and Sources

Because private land has little or no available data, this thesis relies on public data sources. The spatial area of the input must intersect the sample area: a one-mile buffer around the four acquisition targets in the study area. MOSA takes multiple data inputs compiled by the Colorado Natural Heritage Program (CNHP), the Colorado Ownership, Management, and Protection (COMAP), the Colorado Parks and Wildlife (CPW) using the Natural Diversity Information Source (NDIS) methodology, The National Map by United States Geological Survey (USGS), the Federal Emergency Management Agency (FEMA), the Colorado Oil and Gas Conservation Commission (COGCC), Boulder County Parcel/Assessor's Data/GIS (BOCO), and City of Boulder Open Space & Mountain Parks (OSMP). The ecological data are in 90 m and 150 m spatial resolutions, and includes metadata about data collection methodology from 2012. These data must be re-projected from Lat/Long WGS 84 World Geographic Coordinate System to a Projected Coordinate System for Northern Colorado (NAD 1983 HARN State Plane Colorado North FIPS 0501 Feet). The MSOA data sources and their online addresses are listed in Table 3.1. The public data sources are listed in the metadata Table 3.2.

Table 3.1: Public Data Sources that are used in MOSA

Sources:	**Online Address:**	**Agency**
BOCO	https://www.bouldercounty.org/gov/data/pages/gisdldata.aspx	Boulder County GIS Data
CNHP	http://www.cnhp.colostate.edu/download/gis.asp	Colorado Natural Heritage Program
COGCC	http://cogcc.state.co.us/Home/gismain.cfm	Colorado Oil and Gas Conservation Commission
COMAP	http://www.nrel.colostate.edu/projects/comap/	Colorado Ownership Management and Protection
CPW	http://wildlife.state.co.us/Pages/Home.aspx	Colorado Parks and Wildlife
FEMA	http://gis.fema.gov/	Federal Emergency Management Agency
NDIS	http://ndis.nrel.colostate.edu/ftp/	Natural Diversity Information Source
OSMP	https://bouldercolorado.gov/open-data	Open Space & Mountain Parks GIS data
USGS	http://nhd.usgs.gov/	United States Geological Survey

Table 3.2: MOSA Data Sources and Metadata

Name of Data Source	Name of Dataset	Metadata
Boulder County GIS Data	Significant Agriculture Land	The Environmental Resources Element of the Boulder County Comprehensive Plan provides more information in the mapping of the Significant Agricultural Lands.
Boulder County GIS Data	County Parcels	Created from the Boulder County Parcel information layer digitized in parcel fabric from legal descriptions using Coalition of Geospatial Organizations (COGO) data.
Boulder County GIS Data	Critical Wildlife Habitat	3/9/1999 Polygon Attributes: Area - polygon area in square feet Perimeter - polygon perimeter in feet - Wildlife Habitat
Boulder County GIS Data	Significant Riparian Corridors	Boulder County Comprehensive Plan; Boulder County Land-use Department, Boulder, CO. 1986-1987.
Colorado Parks and Wildlife NDIS	Abert's Squirrel	Species Activity Mapping (SAM), general scientific reference using 1:50,000 scale United States Geologic Survey county map sheets.
Colorado Parks and Wildlife NDIS	Bald Eagle	This is part of the Natural Diversity Information Source, drawing on map overlays at 1:50,000 scale United States Geologic Survey county map sheets.
Colorado Parks and Wildlife NDIS	Black Bear	Fall Concentration Areas are defined as those parts of the overall range that are occupied from August 15 until September 30 using 1:50,000 scale United States Geologic Survey county map sheets.
Colorado Parks and Wildlife NDIS	Elk	Observed range of an elk population using 1:50,000 scale United States Geologic Survey county map sheets.
Colorado Parks and Wildlife NDIS	Great Blue Heron	Foraging Areas for Great Blue Heron (Ardea herodias) in Colorado using 1:50,000 scale United States Geologic Survey county map sheets.
Colorado Parks and Wildlife NDIS	Osprey	Foraging Areas are defined as open water areas, typically associated with larger rivers, lakes and reservoirs with abundant fish populations.
Colorado Parks and Wildlife NDIS	Peregrine	Nesting Areas for Peregrine Falcons in Colorado as defined by an area which includes good nesting sites and contains one or more active or inactive nest locations and include a 2 mile buffer surrounding the cliffs.
Colorado Parks and Wildlife NDIS	Wild Turkey	Overall winter range is defined as that part of the overall range where 90% of the individuals are located from 11/1 to 4/1.
OSMP	Property	Property polygons for City of Boulder Open Space & Mountain Parks as COGO defined from legal property descriptions.
OSMP	Potential Areas of Contiguity	Digitized polygons around the city of Boulder as identified in the Boulder Valley Comprehensive Plan.
OSMP	City Limits	Created from the city parcel data layer by query of city limit boundary.
COMAP	Public and Private Land	Public and private agencies donate their GIS data and it is collaborated into the COMaP dataset for distribution.
FEMA	FEMA Floodplain	FEMA: Data included represents Final Flood Insurance Rate Map (FIRM) data that has been published as effective FIRM or DFIRM information.
COGCC	Oil and Gas Wells	The directional map layers are created using data supplied in the directional surveys. .
USGS	Hydrology for Colorado	The NHD is the surface water component of *The National Map*. It contains features such as lakes, ponds, streams, rivers, canals, dams and stream gages.
CNHP	Potential Conservation Areas of Vegetation for Boulder County	CNHP's biologists work throughout Colorado to document critical biological resources in Boulder County

3.3 Modeling Open Space Acquisition Methodology

This study provides a data driven analysis for determining resource-rich locations for potential land acquisition. With the city of Boulder, CO in mind, this thesis authors the MOSA land use model as a potential tool for the Open Space and Mountain Parks real estate division as a supplemental evaluation tool in determining a suitable parcel to purchase for open space. The original MOSA process incorporated one large model that became quite unmanageable. The MOSA model was then broken into nine smaller sub-set models to process the data inputs quickly and analyze the reliability of the model components. The logic behind the MOSA structure is built upon fundamental land use prioritization methods using the goals of Boulder and expert opinion from staff as a guideline of criteria. The top eight ecological priorities of Boulder are represented in eight GIS models. This thesis builds, MOSA using the conflation of *eight class models* plus *one parcel model* to generate raster data layers of various pixel numeric values and score parcels. This list defines the terminologies used to explain MOSA:

- Each *class model* in MOSA has a *class weight* defined by experts.
- Each *class model* has multiple source inputs and converted into raster data.
- Each source input has a *source weight* defined by experts.
- Each model generates *source weighted pixels* of 150 square feet.
- The *source priority* is the *source weight* multiplied by the *source value per pixel*.
- The *class priority* is the *class weight* multiplied by the sum of the *source priorities*.
- The *suitability index* is the sum of source priorities *pixels averaged per parcel*.

These eight class models in MOSA represent riparian corridors that support flora and fauna, keystone wildlife species, oil and gas wells, historical sites, recreational areas of interest, agricultural sustainability, vegetative quality, and parcel proximity in multiple criteria map overlay. Each class model is a topic of consideration and contains multiple *source models*. For example, the wildlife class model has ten inputs of species (i.e., ten source values) where each species is ranked by their endangered criteria and their significance as a keystone species. The vegetation model on the other hand has one input and consists of four classifications of ecological importance. Each class model output enters the final weighted sum by their class weight outlined by the expert opinion of the City of Boulder Land Acquisition Report (2013). The City of Boulder Charter Purposes indicates the goals and criterion of city planners.

Separate class models maintain data manageability and controlled sensitivity screening. Each class model follows a unique weighting strategy created by the experts to generate both the class and source weights, which are defined by qualified staff, spatial analysis and reasoning, popular vote, or city planning priorities and derivatives (Janssen 2001). Compiling available data and applying weighted sum values in land-use modeling targets hot spots of natural resources, thus assisting the decision-making process for land acquisition.

Using the class and source models, MOSA labels each pixel within the study area from priorities 1 (low) to 9 (high). Each parcel in the study area is given a suitability index, which can be interpreted as S for suitability index of a parcel, n as the total number of pixels in a parcel, and X as the sum of source priorities (Riad et al. 2011). S is the suitability index, or average of the combined source weighted priorities per parcel. The value of each raster pixel, X, is derived from the weighted sum tool by the source model methodology in MOSA (Equation 3.1).

Equation 3.1: MOSA Class Priority

$$X = (P_w \times W \quad + P_R \times R \quad + P_E \times E \quad + P_C \times C \quad + P_T \times T \quad + P_A \times A \quad + P_V \times V \quad + P_q \times Q \quad)$$

In Equation 3.1, W is wildlife, R is riparian corridor, E is oil and gas wells, C is cultural, T is recreation and trail connections, A is agriculture, V is vegetation, and Q is property proximity and size. The source weights, $P_w ... P_p$, are based on the values of the elected leadership of the City of Boulder (Table 3.3). The source priorities, W ...P, are generated by each of the source models separately (described in Sections 3.3.2 to 3.3.9). Depending on the number of data inputs, or priority criterion set by city planners, additional class or source models can be added. For example, the current MOSA uses eight models, but if the City of Boulder wants to add a ninth transportation factor, an additional class model named "Roads" would weigh the factors P_{road} and includes sources such as distance to highways, byways, or bus stops. The following priorities are based upon the published Charter Statement of the City of Boulder Open Space and Mountain Parks. In 2013 Boulder city council approved MOSA as a tool in parcel selection. This documentation is available on the OSMP website (City of Boulder Land Acquisition Report).

The MOSA land-use model methodology is detailed in the following sections with explanation of each class model. Open source data is collected from responsible sources, clipped to the boundaries of the defined sample areas, and converted into a raster grid cell through binary values of presence or absence. *Presence is represented by the number 1 and absence is given a 0 and removed from the dataset*. The pixel values of 1 for presence are reclassified according to the data input's source weight. All data input raster cells overlay in the final weighted sum tool where each is assigned its hierarchical significance called its class weight from levels 2-9. The final dataset represents the suitability index of each parcel among the sample areas classified into nine bins of ecological importance.

Table 3.3: City Council Priority Criterion by Rank Order

Data Layer Input	Pixel Value for Presence	Reclassified	Model	Criteria	Min Pixel Value	Max Pixel Value
OSMP Land	Distance in Feet	1-9	Proximity	9	9	324
Habitat Conservation Areas						
Boulder City Limits						
OSMP Parcel size	Size in Acres					
Significant Riparian Corridors	1	8	Riparian	8	32	64
Hydrology		4				
Wetlands		6				
Oil and Gas Wells	1	7	Oil	7	49	98
Bald Eagle Nest Sites	1	9	Wildlife	6	12	54
Preble's Jumping Mouse		9				
Critical Wildlife Habitat		9				
Peregrine Nesting Area		8				
Osprey Nesting Area		7				
Great Blue Heron Nesting Area		6				
Elk Migration Corridor		5				
Wild Turkey		4				
Abert's Squirrel		3				
Black Bear Fall Concentration		2				
Recreation	1	5	Recreation	5	25	25
Significant Agricultural Land	1-4	1-4	Agriculture	4	4	16
Potential Conservation Areas	1-3	1-3	Vegetation	3	3	9
Historical Sites	1	2	Historical	2	4	12

3.3.1 Parcel Selection Model

The parcel selection model finds target parcels outside of the city areas of Boulder and within the sample areas, which are broken into four parts: Table Mountain, Accelerated Acquisition Area, Mountain Parks, and Jefferson County Partnership. The parcel data of Boulder and Jefferson counties are used to identify parcels that are publicly owned or annexed for building development. The vector shapefiles of public lands are erased from the Boulder County data layer. The private parcels remaining are clipped to the sample areas and the city limits are removed (Figure 3.1). The existing private parcels (Figure 3.2) become tagged as potential open space acquisition sites and are classified by priority in the final MOSA weighted sum analysis.

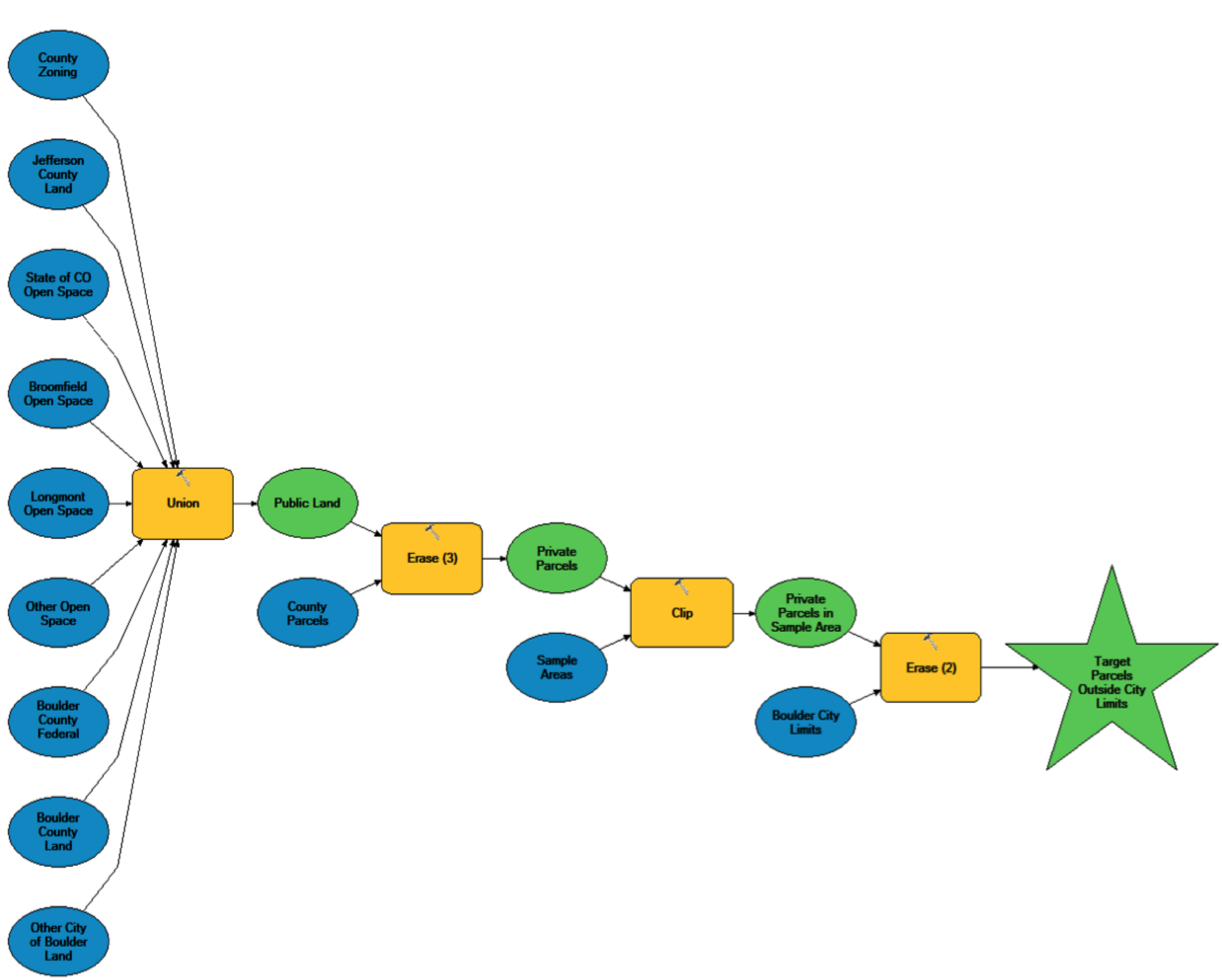


Figure 3.1: Private Parcel Selection Model

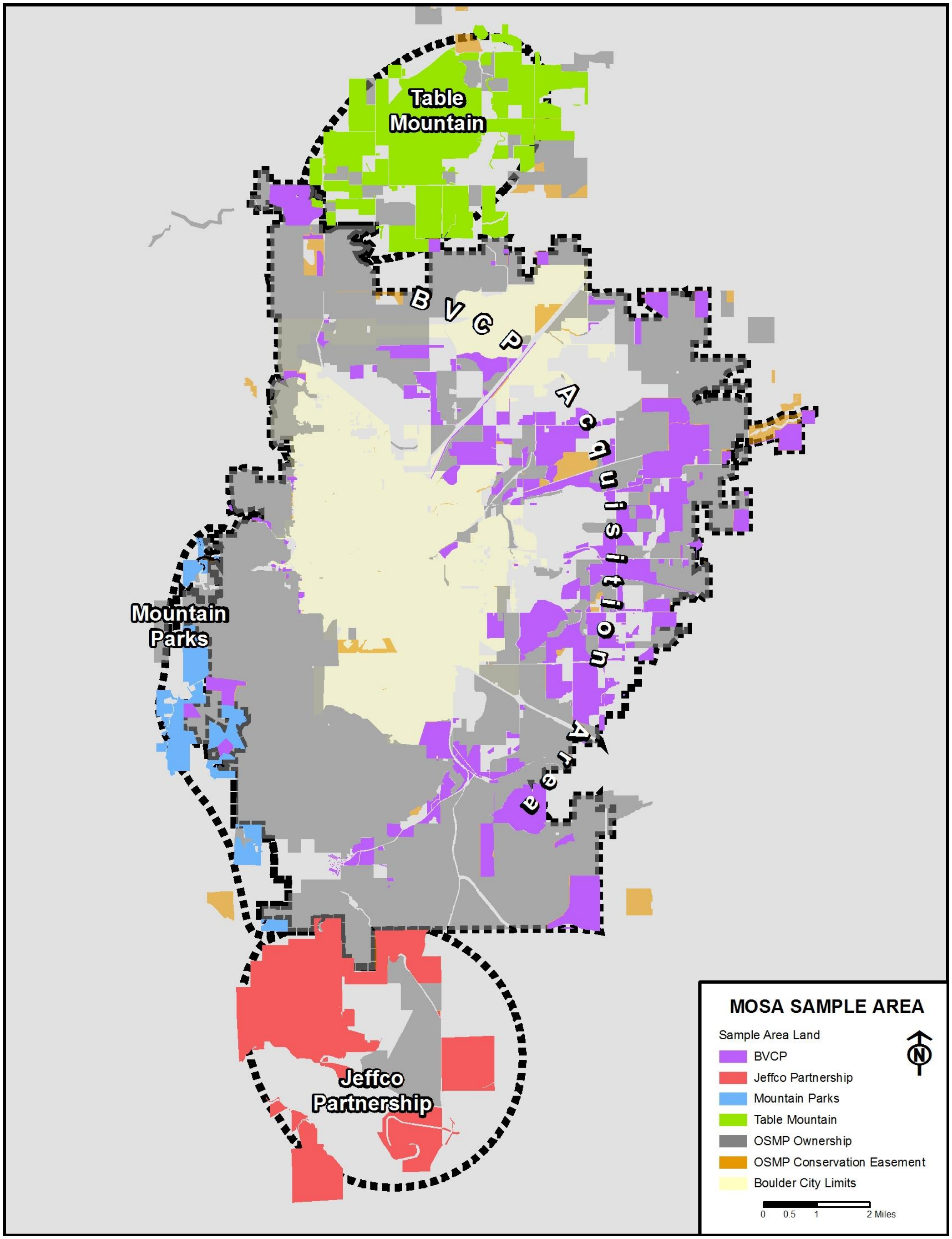


Figure 3.2: The Available Land within the Priority Areas of Boulder, CO

3.3.2 Wildlife Model

Ecological criteria in MOSA are suited for hierarchical structures where prime habitats are ranked by importance according to conservation status assigned by Colorado Parks & Wildlife. Multiple public data sets are available from NDIS and BOCO sources. Spatial layers are selected if they meet the criteria of intersecting any of the four sample areas. The foraging and nesting areas, or the winter and overall ranges, are merged per species. A numeric field is calculated as 1 for presence of a species. The vector data are converted into raster cells and then weighted by *source weights* (Table 3.4). The raster data enters the weighted sum geo-processing tool and each species is ranked by its relative importance and level of threat on a scale of 2-9. The weighted sum tool multiplies the raster cell value by the given priority ranking. The layers of input are then summed per pixel and averaged within the parcel boundaries.

Table 3.4: Wildlife Source Weights in MOSA on a scale of 1-9

Species	**Source Weights**
Bald Eagle	9
Preble’s Jumping mouse	9
Critical Habitat	9
Peregrine Falcon	8
Osprey	7
Great Blue Heron	6
Elk Migration Corridor	5
Wild Turkey	4
Abert’s Squirrel	3
Black Bear	2

The species' rankings (source weights) come from the OSMP ecological staff (Heather Swanson, PhD, OSMP Wildlife Ecologist at *swansonh@bouldercolorado.gov* and Eric Stone, OSMP Resource Information Division Manager at *stonee@bouldercolorado.gov*). The weights are based on their analysis of the Boulder County listing of species of state concern (Hallock 2010). Additional analysis considers the recommendations of the endangerment list provided by Colorado Parks and Wildlife, which classifies species by State Concern, State Endangerment, State Threatened, and Federally Endangered or Federally Threatened according to the US Fish and Wildlife Service. These raster source data enter the final weighted sum with a class weight of 6 (Table 3.3). Figure 3.3 shows the wildlife model species and their hierarchical rankings of importance called their source weights. The minimum pixel value for the wildlife output is 12, where the lowest Black Bear present is a reclassified pixel with a source weight of 2 multiplied by its class criteria 6. The maximum pixel value is 54, where the highest priority of Bald Eagle or Peble's Jumping Mouse present is a reclassified pixel with a source weight of 9 multiplied by its class criteria 6. The wildlife model could produce pixels that are higher than 54 in locations where mulitple species overlap in common space. This model output represents the wildlife contribution in the land use evaluation.

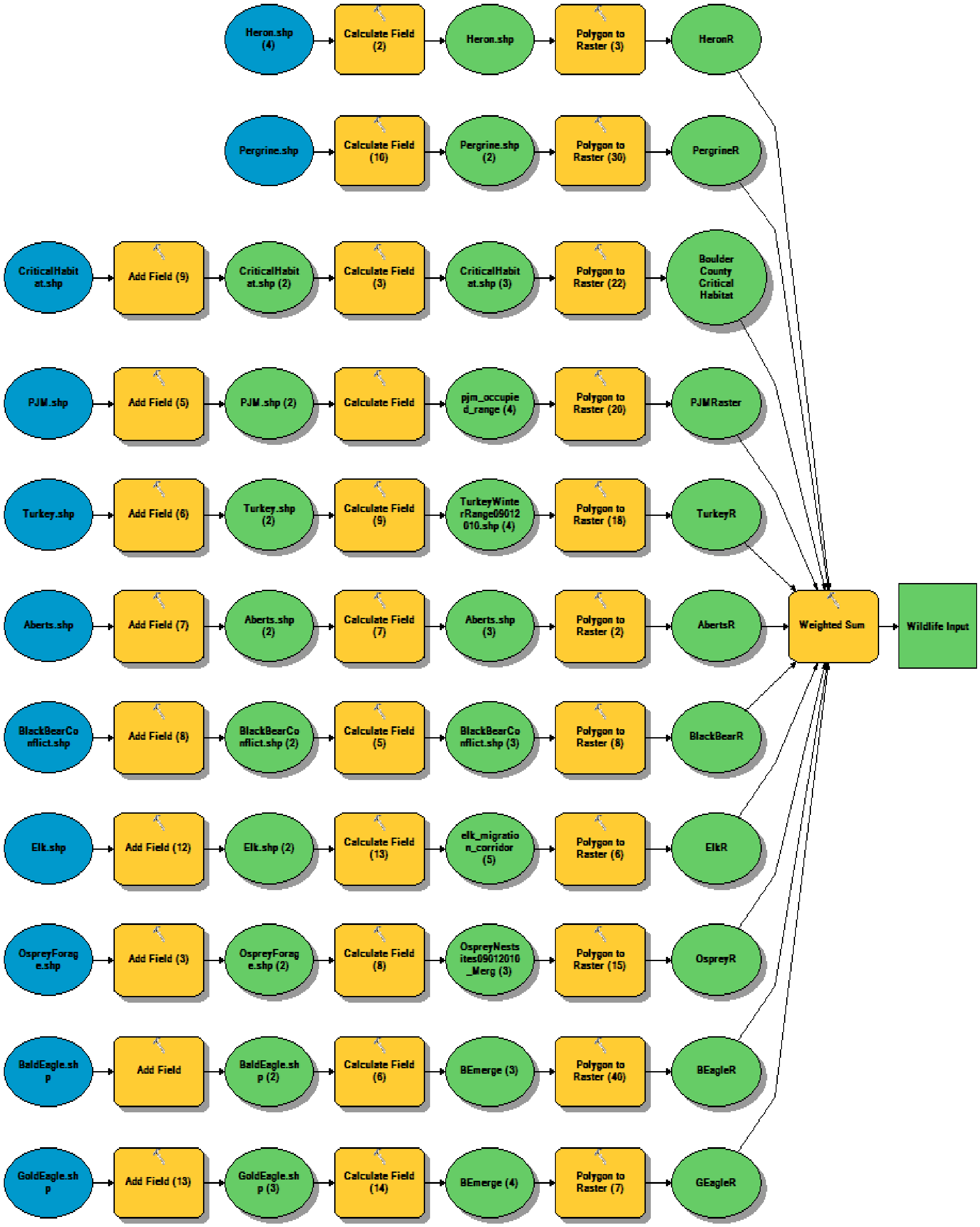


Figure 3.3: Wildlife Model in MOSA

3.3.3 Riparian Model

The digital layers for the riparian model in MOSA include Boulder County wetlands and significant riparian corridors, and OSMP hydrology data. The hydrology linear features are buffered by 150 feet, as identified by the Town Stonington, CT in their land use model to include variations of hydrologic stream flow. Buffering serves the purpose of converting the line data into polygon form to match the other data types. The two wetlands vector layers are merged into one dataset. The sources used in the riparian model are riparian, hydrology, and critical habitat data, which are converted into raster by the numeric value of 1 for presence. The riparian data is placed into a weighted sum tool that ranks the data by factors of importance (i.e., the source weights). The wetlands are weighted by 6, the critical habitat by 8, and the hydrology by 4. The riparian input is given a class weight of 8 in the final analysis (Table 3.5) so the minimum pixel value for the riparian output is 32 and the maximum pixel value is 64. Figure 3.4 is the riparian model in detail while Table 3.5 describes the data source, the conflation procedure, and the source weights of the pixels.

Table 3.5: Riparian Data Structure in MOSA

Data Source	Data Input	Process	Data Type	Raster Value	Source Weights
BOCO	Riparian Corridor		Polygon	1 or 0	8
USGS	Hydrology	Buffer 150 Ft	Line to Polygon	1 or 0	4
FEMA	Floodplain		Polygon	1 or 0	6

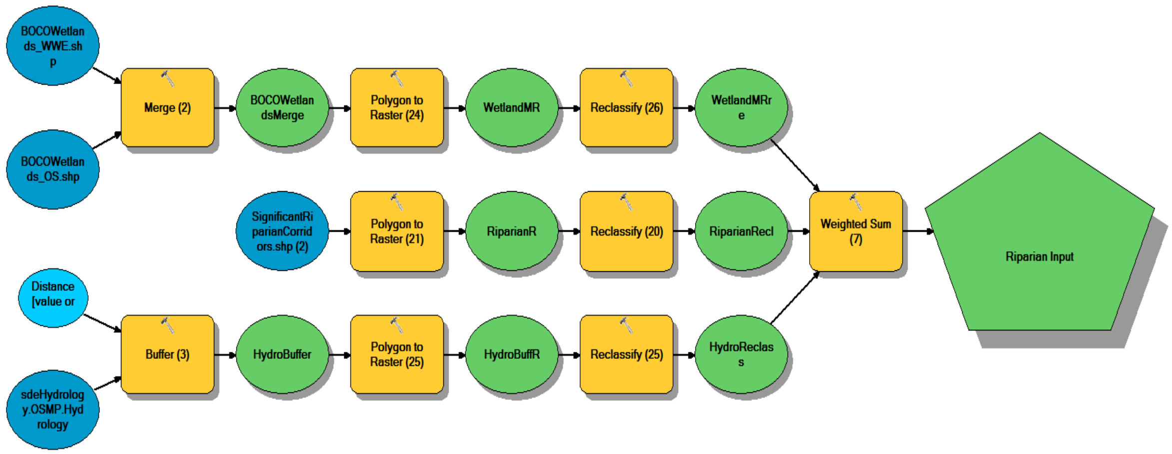


Figure 3.4: Riparian Model in MOSA

3.3.4 Oil and Gas Model

The data layers of the oil and gas model include the point locations of oil well sites in Boulder County as provided by the Colorado Oil and Gas Conservation Commission. The points are buffered by 200 feet around the geographic location to convert the point data into polygons. A numeric field is added to the attribute table and calculated 1 for presence. Zero values are removed from the dataset. The polygon is converted into raster pixels and then reclassified from 1 to its source weight of 7 (Table 3.3). The minimum pixel value of the oil output is 49 (source weight 7 times class weight 7), and maximum pixel value is 98 (two oil wells located within one pixel). Figure 3.5 displays the oil class model in detail.

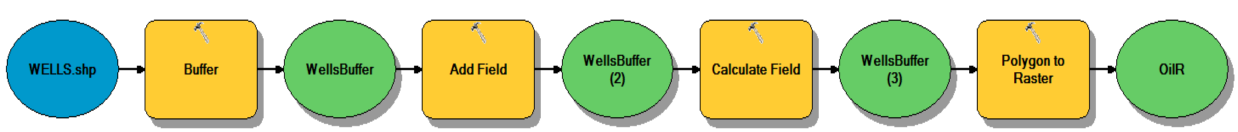


Figure 3.5: Oil and Gas Model in MOSA

3.3.5 Cultural Model

The data layers of the cultural model include the point locations of historical sites in Boulder County. The points are buffered by 200 feet to allow for the area around the geographic location to convert the point data into polygons. A numeric field is added to the attribute table and calculated 1 for presence. The vector data is then converted into raster pixel cells based on this field of presence. The raster is reclassified from 1 as present to its source weight of 2 (Table 3.3). The minimum pixel value for the cultural output is 4 (source weight 2 times class weight 2), and the maximum pixel value is 12 (three cultural sites located within one pixel). Figure 3.6 displays the cultural class model in detail.

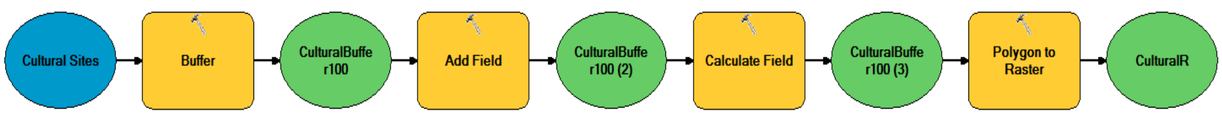


Figure 3.6: Cultural Model in MOSA

3.3.6 Recreation Model

Ecologists agree that protecting isolated natural areas is only a beginning to functional urban design. When connecting metropolitan areas there are two primary objectives, the first is ecological and the second is human (Forman 1995). Sustainability goals of Boulder include the connectivity of regional and local trails. In the MOSA model the data layers include three inputs: digitized areas of trail connections identified by the City of Boulder City Council in 2012, areas agreed upon in the Boulder Valley Comprehensive Plan, and areas of connections between trails less than two miles apart that represent potential contiguity. The three inputs are merged and converted into raster data with a binary value of 1 for presence or 0 for absence. The raster pixels are reclassified from 1 as present to its source weight of 5 (Table 3.3). The minimum pixel value for the recreation output is 5 and the maximum pixel value is 25, (presence source weight of 5 multiplied by its class weight of 5). Figure 3.7 displays the recreation model in detail.

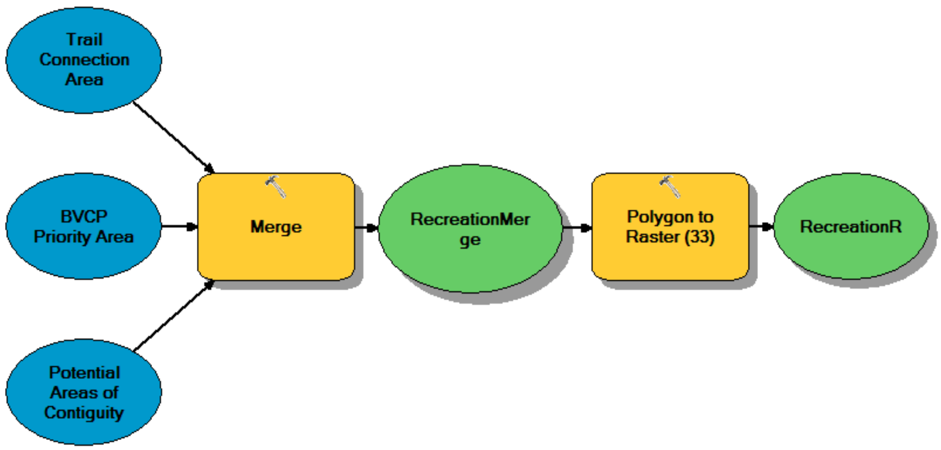


Figure 3.7: Recreation Model in MOSA

3.3.7 Agriculture Model

The data input for the agriculture model is from the Boulder County website and represents four categories of significant agricultural land in Boulder County: 4 as very significant to 1 as low significance. A sustainable agricultural economy is an integral part of Boulder County's long range planning. The vector layer is converted into raster pixel data based on this classification of 1-4. The minimum pixel value for the agriculture output is 4 and the maximum pixel value is 16 (source weight 1-4 times class weight 4). Figure 3.8 displays the agriculture class model in detail.

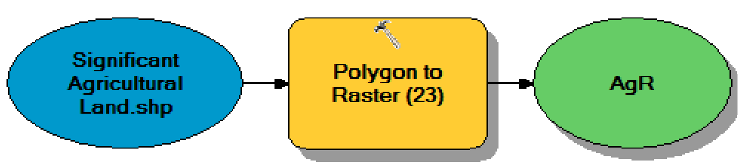


Figure 3.8: Agriculture Model in MOSA

3.3.8 Vegetation Model

The Colorado Natural Heritage Program sponsored by Colorado State University provides the digital data for potential conservation areas in Colorado in three classifications: 3 being the most critical to 1 being somewhat critical. The vector polygons are converted into raster pixel data by its source weight of 1-3 and then multiplied by its class weight of 3 (Table 3.3). The minimal pixel value from the vegetation output is 3 and the maximum pixel value is 9. The vegetation class model is detailed in Figure 3.9.

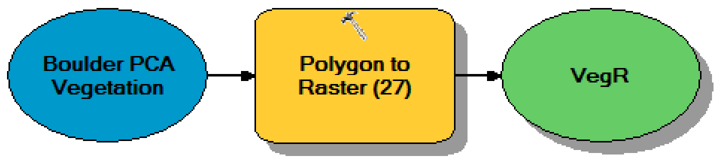


Figure 3.9: Vegetation Model in MOSA

3.3.9 Proximity Model

The proximity model consists of near distance and size measurements of available parcels. The near tool measures the direct distance from the parcel centroid to its nearest neighboring polygon (parcel). The OSMP property data layer is used to calculate distance in feet from each available parcel to the nearest OSMP land, OSMP habitat conservation area, and to the centroid of Boulder city limits. The area of each available parcel is calculated in square feet. These three proximity distance inputs and one parcel size input are reclassified on a scale from 1 to 9, nine as the closest or largest parcels and one as the furthest or smallest parcels. The polygons are converted to pixels based on their 1 to 9 nearness and size classes. The four proximity inputs enter the weighted sum with a source weight of 1 so that they retain their 1-9 classifications. Figure 3.10 details the proximity model and its three near distance and one size reclassifications.

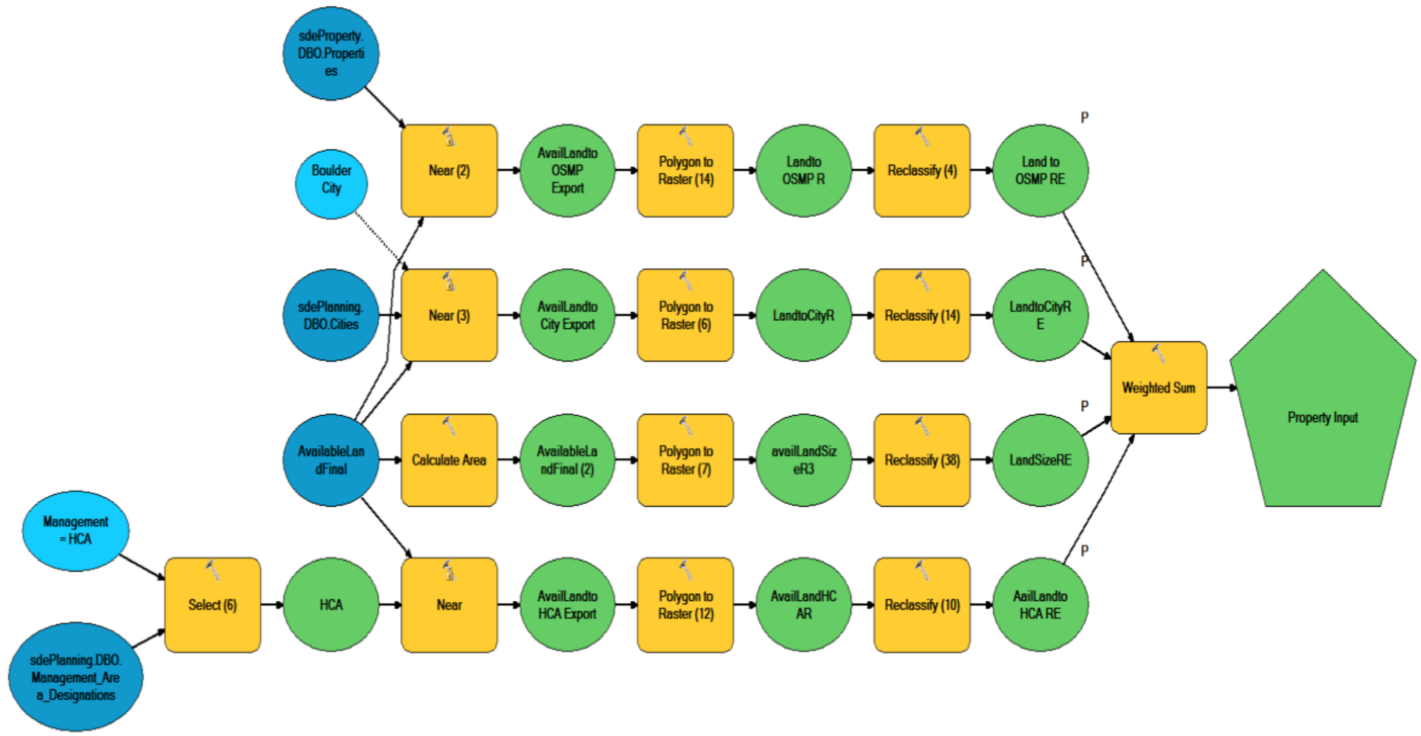


Figure 3.10: Proximity Model in MOSA

Table 3.6 samples the MOSA reclassification methods where the distance and area in feet are converted into integers and reclassified from 1-9. The pixel value of the raster data becomes nine when closest in feet to the selected neighboring parcels and lessens to one when furthest away. The area of each parcel is measured in acres and then reclassified into sizes from 1-9. The largest bin of property size is reclassified as nine, moving downward to the smallest property size as one. The three proximity inputs and the parcel size input enter the weighted sum tool where they are layered and multiplied by a source weight of 1. This proximity layer enters the final class model as the proximity input. The proximity input is given the criterion ranking of 9, as noted in Table 3.6 as *"Original Class Weight".* This methodology assigns heterogeneous pixel weights to different parcel proximity criterion, recognizing the diverse aspects of spatial options that contribute toward decision objectives (Ligmann-Zielinska 2012). The minimum pixel value of the proximity input is 9 (least source weight 1 times the four data inputs, times its class weight 9), and the maximum pixel value is 324 (max source weight 9 times the four data inputs, times its class priority 9). The mean pixel value per parcel is calculated using the zonal statistics method. The average parcel pixel value, called its suitability index, is divided into nine natural breaks among the sample area using Jenks classification method. The parcel suitability indices range from 46-1,672 and are detailed in Table 3.7 on page 38.

Table 3.6: Reclassification Examples of the Proximity Model in MOSA

Parcel ID	Nearest Feet to HCA Land	Reclassified Value of HCA Distance	Nearest Feet to OSMP Land	Reclassified Value of OSMP Distance	Nearest Feet to City Limits	Reclassified Value of City Distance	Size of Parcel Acres	Reclassified Value of Size
100	75.22	9	145.84	9	124.82	9	1056.75	9
101	350.78	8	244.87	8	251.08	8	842.24	8
102	504.92	7	488.35	7	378.99	7	777.54	7
103	777.81	6	572.13	6	628.71	6	598.31	6
104	869.24	5	652.85	5	759.12	5	487.22	5
105	1054.11	4	724.68	4	816.77	4	322.46	4
106	1204.87	3	899.45	3	1089.64	3	266.52	3
107	1857.39	2	925.69	2	1487.33	2	108.59	2
108	2157.32	1	1114.10	1	1712.45	1	54.96	1
Source Weight	1							
Original Class Weight	9							

3.3.10 Classification Methods

In the following paragraphs, Jenks Natural Breaks Optimization method classifies the MOSA pixels within the study area by breaking classes between large gaps of ecologic values. In comparison, Quantile classification predefines the nine classes used and ranks the pixel value by placing an equal number of observations into each class.

As seen in Figure 3.11, more pixels in the sample area are showing as ecologically rich because the classification bins are filled with an equal number of entries. The advantage to using Quantile class breaks is that each pixel is represented equally in the final map, but its disadvantage is that it leaves large gaps between levels of observations. In some cases, one classification interval is overrepresented. For this reason, Quantile classification is not used in MOSA. The clustering of ecologically rich land is better represented by the Jenks classification method.

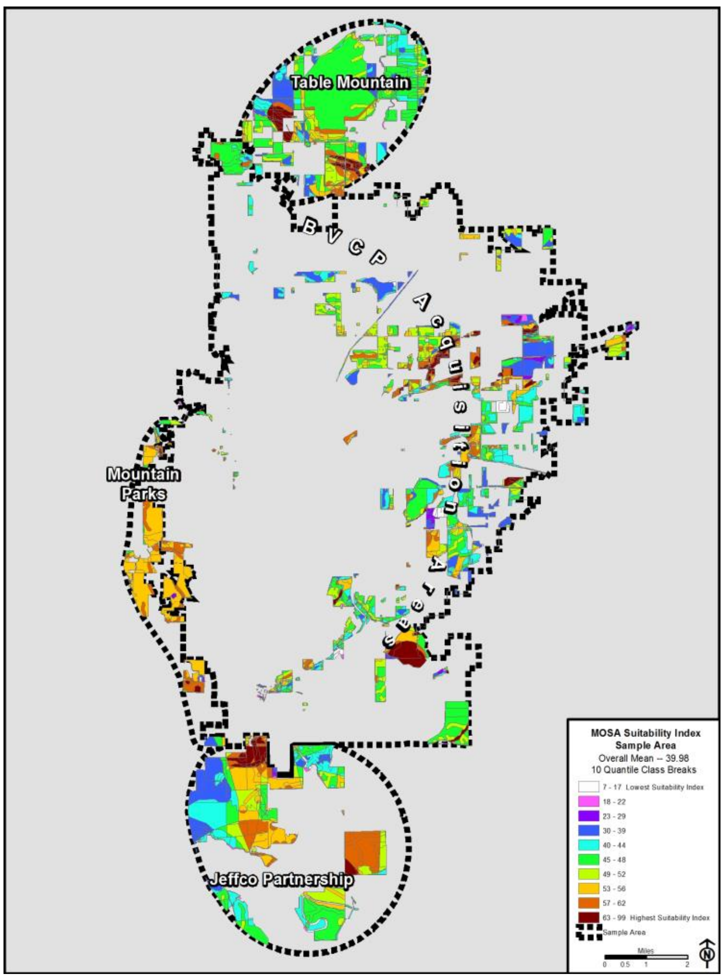


Figure 3.11: Quantile Classification Method upon Pixels

Jenks classification method works well in MOSA because it iteratively determines the best possible arrangement of observed values by locating natural breaks in the spatial distribution of pixel numerals. Clustering occurs around the median pixel value, but above the mean is where the spatial distribution begins to display these natural breaks, identifying pixels that are exhibiting above average ecologic natural resources within the parcel that could be targeted for open space purchase. Jenks Optimization Natural Breaks is shown with gradient symbology in the choropleth map in Figure 3.12; dark red is high natural resource areas where pink is lower natural resource areas (see Appendix A).

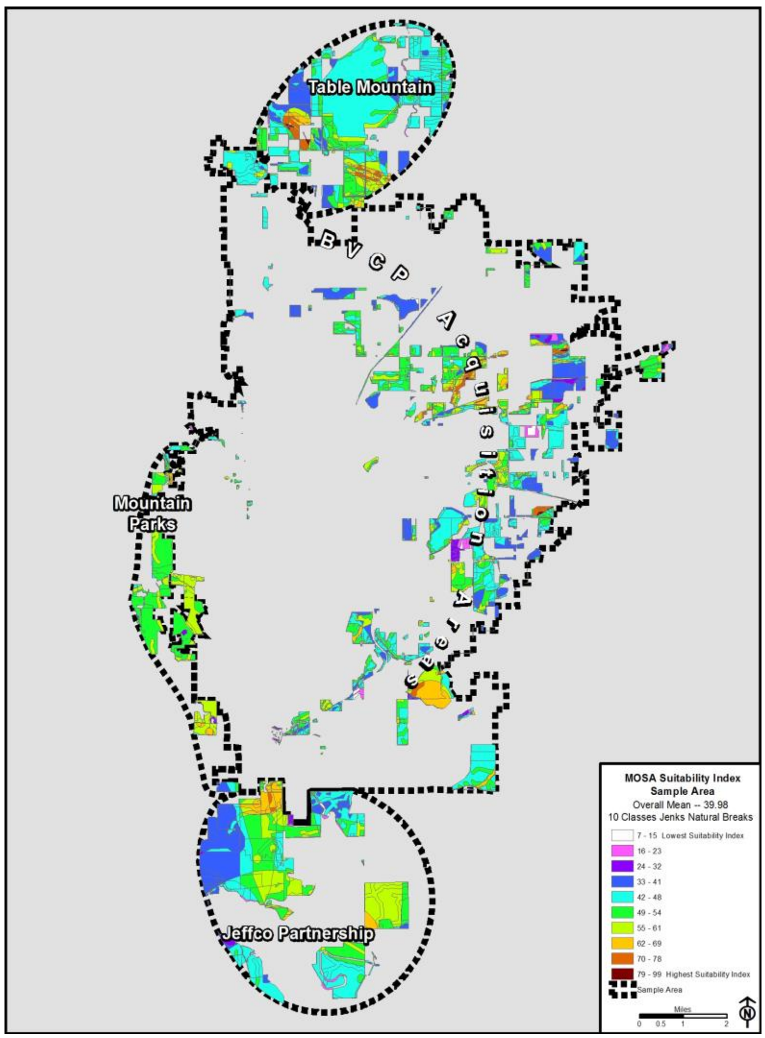


Figure 3.12: Jenks Natural Breaks Classification Method upon Pixels

3.3.11 Final Weighted Criteria Model

The final weighted analysis is performed by multiplying the sum of stacked pixel values from each sub-set model by its class priorities defined by the expert decision makers. The absolute pixel values are averaged within the parcel boundary and are called the parcel's suitability index. Each parcel within the study area is classified into one of nine bins of suitability indices, or their ecological contribution, according to Jenks Natural Breaks classification method. The parcels in the top four levels are selected for further analysis.

The numeric quantity of the pixel represents the quality of land ecologically, ideally representing the parcel's environmental service toward human health. The final output is masked or extracted by the available land parcel layer (created from the parcel selection model, Figure 3.1) and individual parcel suitability index is calculated using Equation 3.1. Figure 3.13 displays the class models feeding into the final weighted sum tool of MOSA and weighted according to the criterion set by the expert, or city planners of Table 3.3. The minimum pixel value for the final weighted sum output is 46 and the maximum pixel value is 1,672 as graphed in Figure 3.14. The nine classification bins of suitability indices among the available parcels are listed in Table 3.7.

Table 3.7 Original MOSA Parcel Suitability Indices using Jenks Classification

Parcel Suitability Index	Pixel Value
Lowest	46-331
	332-530
	531-689
	690-818
Mean	819-946
	947-1078
	1079-1200
	1201-1398
Highest	1399-1672

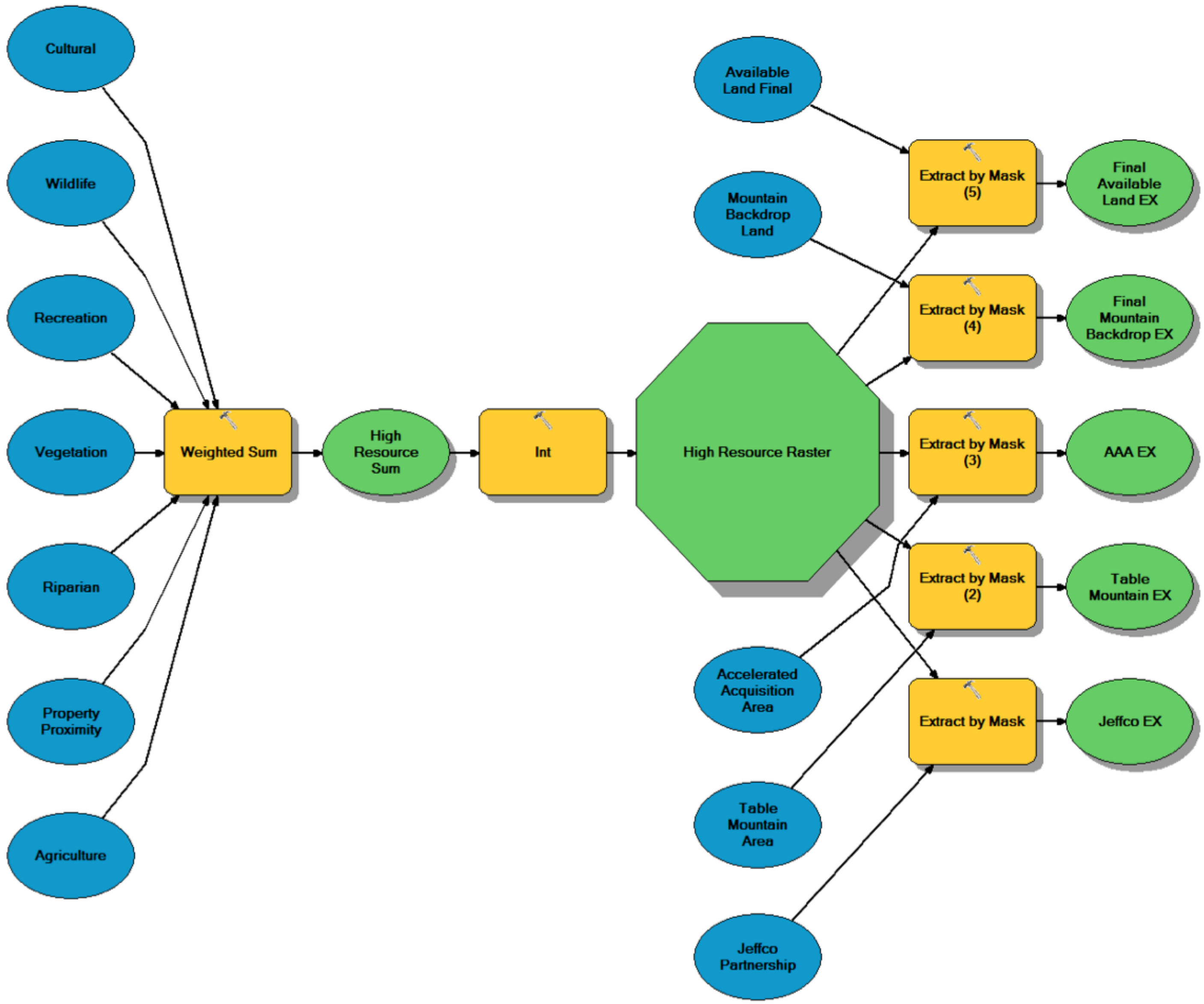


Figure 3.13: The Final Weighted Class Criteria Model in MOSA

Figure 3.14 shows the zonal statistics per sample area using the Jenks Natural Breaks classification method. The Jefferson County Partnership area scored the overall highest maximum range of property ecologic values. The BVCP area was the second highest scoring, Table Mountain area was the third largest range, and the Mountain Parks area scored fourth among the sample areas. The highest average mean of ecological resources is found in the Table Mountain sample area. Parcels in the Jefferson County Partnership have the greatest suitability index with the greatest range, most likely due to its wildlife corridor, multiple eagle nests, intersecting riparian areas, and large parcels contiguous to existing open space.

AcqAreaNam	MIN	MAX	RANGE	MEAN
Mountain Parks	62	1268	1206	246
Jefferson County Partnership	46	1672	1626	490
Table Mountain	46	1523	1477	684
BVCP Acquisition Areas	49	1581	1532	84

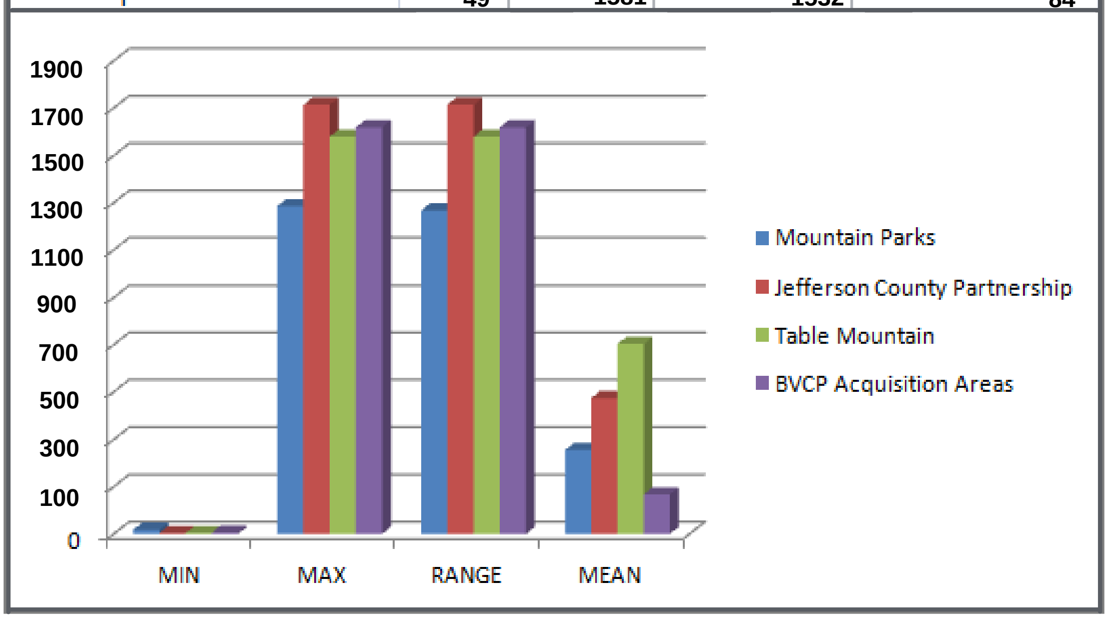


Figure 3.14: Zonal Statistics and Distribution of MOSA Data by Sample Area

Figure 3.15 is an example of a useful form showing how the results of MOSA can be combined with other data to aid the parcel acquisition decision-making process. The parcels in the top four levels from the Jenks Natural Breaks Optimization are targeted and compared to its economic demand. The open space parcel rating sheet is a clean and convenient way of quantifying the carrying capacity of a particular parcel while weighing the pros and cons of acquiring it.

Figure 3.15: Example Open Space Parcel Rating Sheet

Parcel Name: ____

Parcel Number: ____

Date of Analysis: ____

Acquisition Area: ____

Suitability Index: _______________

Priority Ranking: _______________

Sub-Class Ranking by Factor:

Parcel ID	Wildlife	Riparian	Oil/ Gas	Historical	Recreation	Agriculture	Vegetation	Proximity	Suitability Index
100	64	52	18	12	47	22	30	84	329

Overall Ranking:

Parcel ID	Suitability Index	Zonal Statistics Ranking	Market Value of Parcel	Asking Price of Parcel	Incentives for Parcel Purchase	Total Price of Parcel	Decision
100	329	High	500,000	550,000	$10,000	560,000	Yes

Notes:

Zonal Statistics Criteria:

This classification is the range of mean suitability index among the acquisition areas

Priority	Accelerated Acquisition Area	Table Mountain	Mountain Backdrop	Jefferson County Partnership
High				
Medium				
Low				

CHAPTER FOUR: MOSA RESULTS

In this chapter, section 4.1 presents the experiment results using MOSA for identifying potential private parcels for open space acquisition based on the original theoretical criterion from the City of Boulder. Private parcels with the greatest ecologic resource are determined by the Jenks Natural Breaks classification method of *the average pixel value per parcel* within the study area. This section also presents the recommendation of an adjusted criterion ranking that improves the efficacy of the final output.

4.1 MOSA Results in Detail

Using the original criterion provided by the City of Boulder this study identified 1,024 private parcels within the four sample areas that display potential for open space acquisition. MOSA classifies the ecological richness of these private parcels by averaging the pixel values within each parcel. The parcel average ranks its suitability index for open space conservation. The averages are separated into nine classifications using Jenks Natural Breaks; one being the lowest suitability index, and nine being the highest. The 415 parcels in the top four levels are detected and further evaluated for potential open space acquisition. For the purpose of this thesis the original analysis uses the criteria (i.e., both the source and class weights) set by a theoretical City of Boulder council and results in clustered spatial distributions throughout the sample areas.

Figure 4.1 displays the 415 targeted parcels within the combined sample areas that score a suitability index of 6, 7, 8, and 9 from the Jenks classification in the original land-use weighted criterion. MOSA found these parcels ecologically desirable with above average natural capital and could become a top priority for open space acquisition. These results suggest reasons for spatial clustering among the MOSA output that is not occurring randomly, but because the parcels possess, or are contiguous to ecologically rich land. These private parcels identified as the four top classes in Jenks deserve recognition, investigation, and potential open space acquisition. These findings serve as explanatory evidence for city planners when comparing ecological and economic land values for the intent of parcel prioritization for open space land.

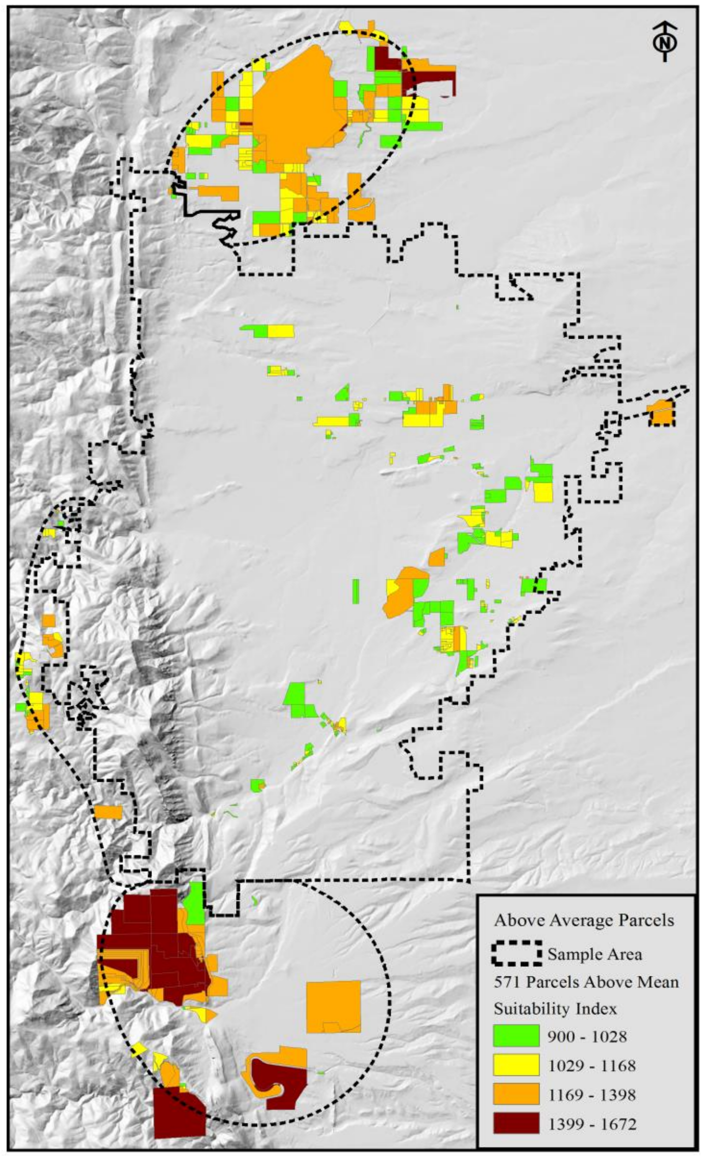
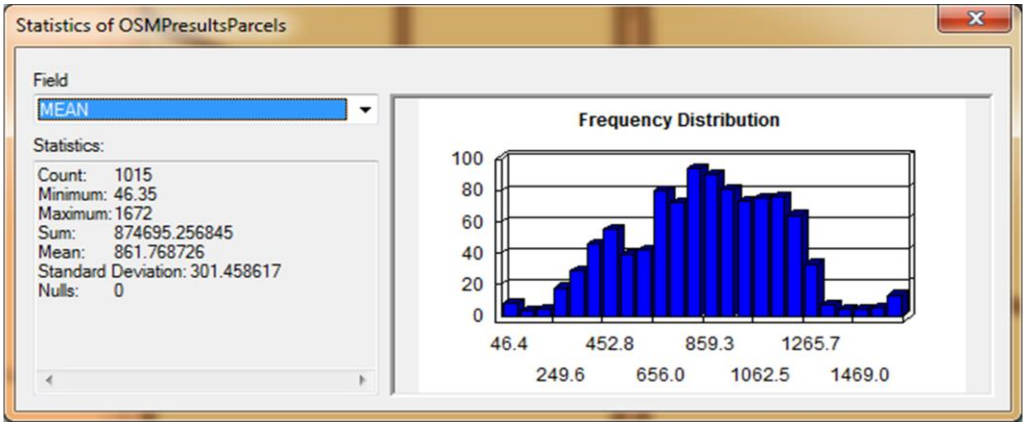


Figure 4.1: MOSA Targeted Parcel Spatial distribution of parcel suitability indices using the *original* criterion

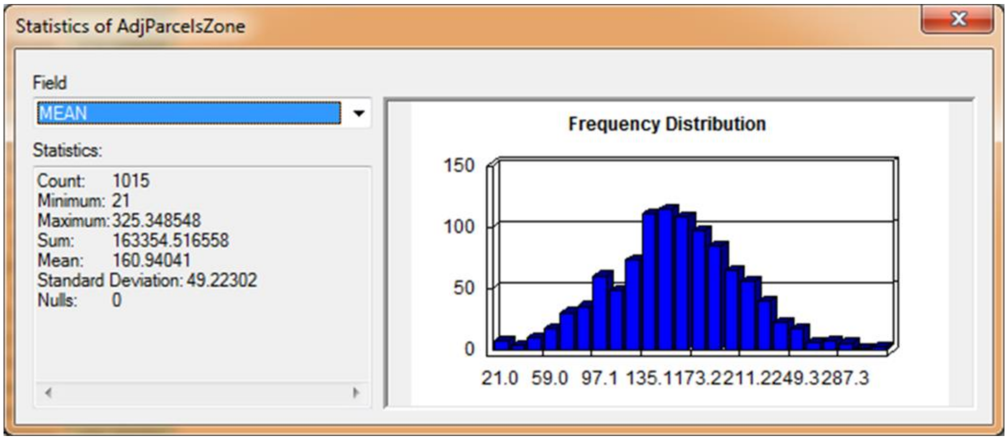
Subjectivity is inherent in any expert-based model and should be recognized as potential for creating model bias (Goodchild 1998). *Original* theoretical criteria set by the City of Boulder Charter Purpose (Table 3.3), prioritizes parcel proximity as the top ranking of class weight 9, but this weight is much too heavy in the final criteria. The parcel proximity pixel value inflated the final dataset and dissipated the other model inputs. Without the proximity input, the range of suitability indices for parcels within the study areas ranged between 4 and 184. With the proximity input included the suitability indices raised from 4 to 1,817. The proximity input was close to ten times the volume of the other data inputs when summed in the final criteria ranking. This bloating of suitability indices indicate bias in the MOSA model where the proximity input was negating the influence of the other seven datasets. The influence of a parcel's proximity to other ecologically rich land should be reduced so that it is closer in weight to the other data inputs.

One way to reduce the proximity output is to diminish the source weights in the proximity model by a tenth of their original level. In the *adjusted* theoretical criteria the first proximity nearness parameters is assigned the source weights of .5 to habitat conservation areas instead of 5, .4 to existing open space land instead of 4, .2 to city center instead of 2, and the size of the parcel is weighted by .3 instead of 3 (Table 3.6). The pixel value is much smaller in this model scenario and reduces the overwhelming presence of the proximity model by one tenth in the final weighted sum. After sensitivity testing was performed upon each data input by iterating its class weights within the weighted sum tool, it is recognized that the datasets are most proportionate in relation to each other when reducing the mass and class priority of the proximity model. The adjusted results reflect the class weight of the proximity model as level 2, cultural as level 3, vegetation as level 4, agriculture as level 5, recreation as level 6, wildlife as level 7, oil as level 8, and riparian as level 9.

The following paragraphs detail the results of the MOSA *original* criterion analysis against the *adjusted* criterion analysis. The spatial distribution of the original MOSA class and source weights is clustered in the above average classification as shown in Figure 4.2. The proximity input is classifying more parcels as ecologically rich the greater the weight criterion, which means bias in the model parameters because not every data input is contributing effectively in the weighted results. The spatial distribution of the adjusted weighted criteria after the sensitivity analysis had fewer parcel clusters in the higher classifications and is more bell-shaped curved approximating normal distribution.



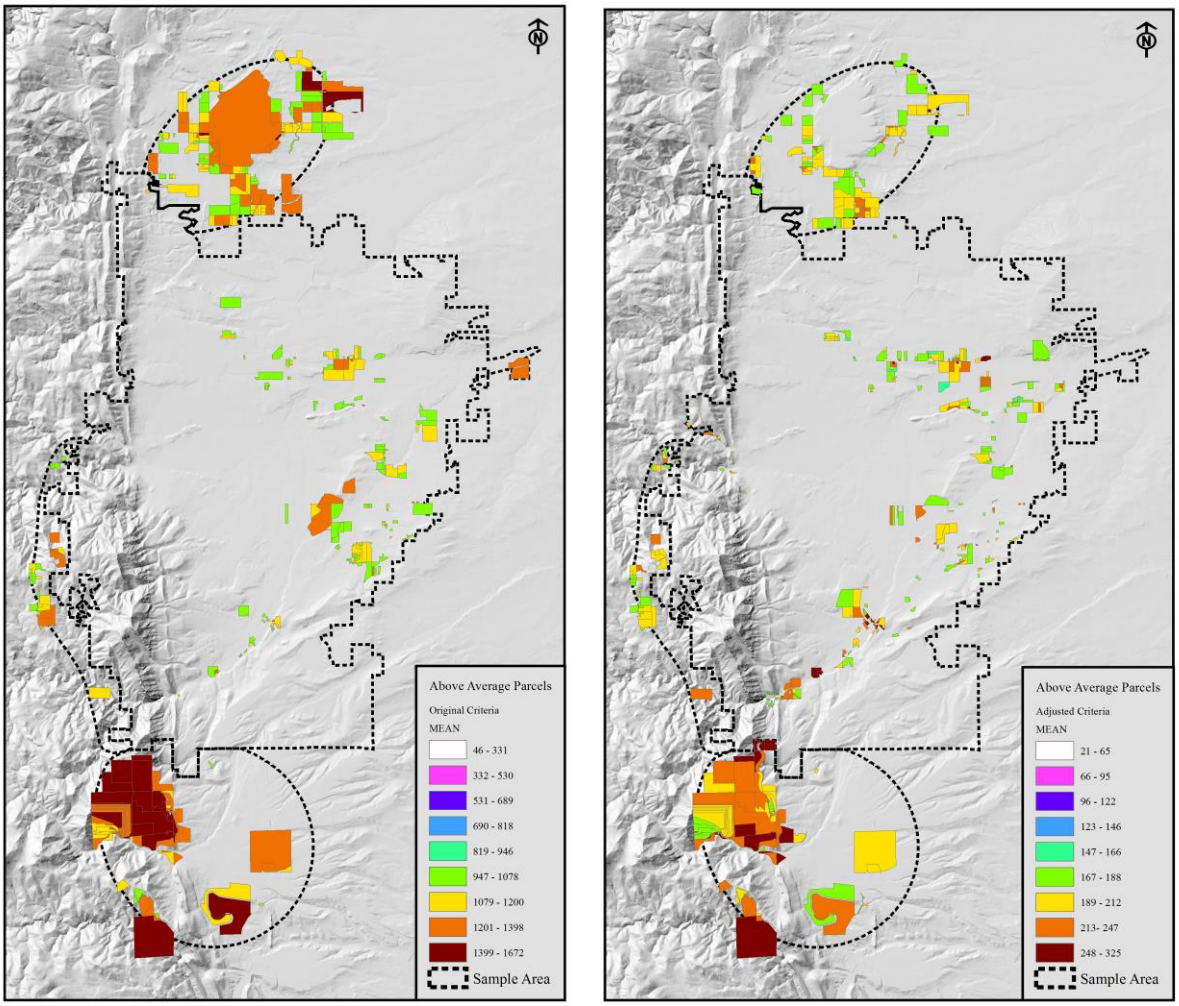
Spatial distribution of parcel suitability indices using the *original* criterion



Spatial distribution of parcel suitability indices using the *adjusted* criterion

Figure 4.2: The Spatial Distribution Comparison of Parcel Suitability Indices

The differences between the original model criteria and the adjusted criteria are displayed in Figure 4.3. The selected parcels are chosen from the top four classes of Jenks. In the original model there are 415 parcels that are classified as having above average ecological resource, but the sensitivity testing suggests that this model outcome is biased toward the proximity model parameters and fails to adequately represent the underlying data layers. After adjusting the class and source weights of the proximity model, the number of above average parcels increases to 457, and they were different parcels than from the original outcome. This could be from the other ecological datasets becoming meaningful in the final weighted distribution. The output from the adjusted model is more representative of the full spectrum of data and is best suited for this weighted criteria analysis (see Appendices B and C).



Original weighted criterion results

Adjusted weighted criterion results

Figure 4.3: Parcel Criterion Comparison

CHAPTER FIVE: FUTURE WORK AND CLOSING DISCUSSION

Future model modifications and spatial autocorrelation are discussed in section 5.1, while section 5.2 concludes this thesis by discussing the multiple benefits of land-use modeling for open space prioritization.

5.1 Future Model Considerations and Limitations

An additional function of the MOSA model includes dynamic interactions between conditional responses of model elements in reaction to their environment. For example, this land use model considers wildlife habitat and recreation corridor in the weighted sum evaluation as presence or absence, when in actuality the wildlife highly suitable habitat may decrease with the presence of trails or human impact. The more sophisticated land-use model would respond to the presence of impacting anthropogenic factors like roads, noise, or traffic volume and would react negatively according to the scale of impact. The resulting product of each pixel would vary dynamically and stochastically as various factors interact within variations of model criteria. For example, this would include buffering trails and roads by a certain threshold of impact and then building an algorithm that estimates a parameter of stress-response. The area of impact is found in the intersection of the trail or road buffer overlapping with other ecologic inputs. These effected pixels within the impact area would lessen in value stochastically (Wu et al, 2007).

A second consideration is that the model developed for this study does not consider the parcel owner's willingness to sell their land. Veto threshold survey data collected over the sample area would include the parcel owner's willingness to sell their land at market value, above market value, or not willing to sell their land at any given price and only the available parcels would be considered in the final analysis.

Overall results indicate the proximity input class model is rather heavy for the overall weighted sum and could be reduced by a tenth to equal the lesser inputs. An additional parameter to alleviate the overweighed proximity input is adding a near distance table for every class model, to measure its location to existing open space land, habitat conservation area, and city center. The value for each feature class would then be increased depending on its proximity to the same feature class in other pixels. The existing proximity model measures near distance from each parcel to existing open space, habitat conservation areas, and city center, and considers parcel size, and then classified as 1-9 in the proximity model and given the criteria weight of 9. Every ecological input could also be measured in nearness to existing open space land, habitat conservation area, city center, and its size, and then reclassified as 1-9 in the final weighted sum with the criteria weight for each input found in Table 3.3. For example, the size and location of an existing riparian area in relation to habitat conservation areas could be classified in near distance tables like the parcel proximity. This method would increase the pixel value of each ecological input in the final weighted output with its presence and nearness classifications in the criteria analysis so that potential scores on all measures would be more evenly weighted.

Subjectivity testing as mentioned in this thesis suggests the proximity model is sensitive among the other inputs because of its spatial volume (spatial autocorrelation exists in other input and is explained next in this section). It is recognized that the proximity model displays clustered spatial distribution and is notably very influential to the land-use model prediction. These clusters are lacking randomness and could be explained by the nearest neighbor likeliness among ecologically rich areas like riparian wetlands, wildlife corridors, and the parcel proximity in relation to existing open space land. The ecologically rich lands are most likely near river systems or drainages where flora is present and wildlife has viable food and water sources. The City of Boulder city council approved MOSA with the original criterion rankings where the proximity model is the primary influence in the parcel classifications. This research suggests modifying future analysis by the adjusted criterion levels so the eight ecological input datasets are most equally considered in the final weighted sum suitability index.

Spatial autocorrelation measures the degree to which spatial clustering itself explains change in dependent variable values. It is based on the idea that near subjects within the sampled area are more likely to have similar values than are subjects further apart (Tobler 1970). When spatial data display autocorrelation, it is possible, at least in part, to predict the pixel value at one location based on the pixel value sampled from a nearby location. In the MOSA model developed for this thesis, clustering patterns within the sampled area may be evident and may often be due to the likeliness of nearby ecologic values. Autocorrelation can be explained by dependent and independent responses to the variable’s surroundings. For example, a plant may thrive in an area where its dependent soil, water, and air temperature are ideal for its survival. This location is more likely to support an abundance of plant life than other areas that are less ecologically suited. Wind speed may interact with the soil or air temperature disrupting the reproductive cycle of the plant. The plant abundance variable is both dependently and independently autocorrelated to itself under a given circumstance. Both influences result in similar values of plant abundance or plant disparity each in close proximity and in distance.

In this land use criteria model, the pixel values on each measure may not be fully independent of themselves or of their locations. In fact, it may be the case that the clustered ecologically rich parcels in the top four classifications are displaying spatially autocorrelation. For example, the further the parcels are from protected land, the less likely they will score well for the ecologic contribution to their suitability index. The proximity variable is already over-weighted in the model and it may be inherent in some of the ecological variables as well. This may also be creating biased clusters of highly suitable parcels overly dependent upon nearness and size parameters over other influences in the model and skewing the results. At the very least, it is not possible to say that the weightings dictated for the model are being carried out with precision. Further autocorrelation and statistical examination of this land use model would be beneficial in testing its reliability to determine whether the highly suitable parcels remain clustered after the proximity parameters and the influence of proximity itself are lessened in the final weighted sum. The latter results could further explain consistently high suitable parcel clusters near dependent ecologically rich riparian areas, wildlife corridors, river systems, and trail connections even after the proximity criteria are reduced.

5.2 Closing Discussion

Scientific analysis of weighted criteria for open space acquisition requires modeling that is adaptive with interchangeable data layers, functional with consistent results, and replicable for others to adopt. The final weighted sum in this example of land use prioritization considers nine class model criteria that are interchangeable and flexible as city planning priorities adapt over time. This research model is adaptive because each input is contained within its own model and data can interchange easily. It is functional because the model output serves as supplemental evidence in prioritizing open space acquisition for ecological preservation, inherently improving the intrinsic value of the community that it serves. It is also replicable because it is simple and straightforward by design. The weighted criteria of a functional land-use model should be interrogated through sensitivity testing. This is done stochastically or intentionally by generating various model outputs based on iterated changes to the set criteria within the weighted sum tool. The sensitivity testing will validate the strength and weakness of variable relationships and expose model bias so adjustments can be allocated to the final model criteria. Given the effectual association between land acquisition and the planning context, analysts should use land-use models when examining future open space acquisitions (Gerber 2012). Often land is coveted for its economic value, but ecological values are neglected due to a lack of information or concern by city planners. In multi-criteria decision analysis, expert planners can vary their criteria ranking by prioritizing the changing values of a community. Even when a community agrees on supporting open space acquisition, strategic methods should be followed when choosing parcels to preserve. Public ecological data is often coarse, but at least offers a glimpse of reality in private areas where data is limited.

Open space can be defined as land that is not developed yet and provides a valued habitat for humanity to coexist with its flora and fauna. It is the working landscape of forests, farms, scenic byways, greenbelts, natural areas, and wetlands, each synergistically contributing to the intricate web of ecological balance with minimal human impact. Open land can be acquired and preserved for the well-being of current and future generations. It is the right and responsibility of a given community to protect hedonic nature from anthropogenic affliction (Speth 2008). This is done through a proactive public process, like voting for open space acquisition by using city sales tax allocation. The open space land that is acquired and managed by a governing agency can have above average ecological value and be stringently tested under the parameters of a land-use model that quantifies the natural resources present.

In conclusion, this thesis creates, defines, and develops the Modeling Open Space Acquisition, expert-based, multi-criteria, decision making model, to identify and quantify a parcel's ecological natural assets for the purpose of prioritizing private parcels and preserving public open space. The priorities of city planners can be ranked by criteria in a GIS environment to scientifically evaluate the carrying capacity of a given parcel prior to purchasing it. Evaluating the ecologic potential of a parcel before acquiring it can eliminate the costly expense of purchasing land that is low in ecological resources and requires costly restoration or extreme management. Land use modeling is an important tool in detecting ideal areas for future open space acquisition by modeling the spatial relationships between ecologically rich parcels and their proximity to contiguous open space lands. Ecologically rich parcels can be investigated more closely and become a top priority for the City of Boulder to acquire and preserve as open space.

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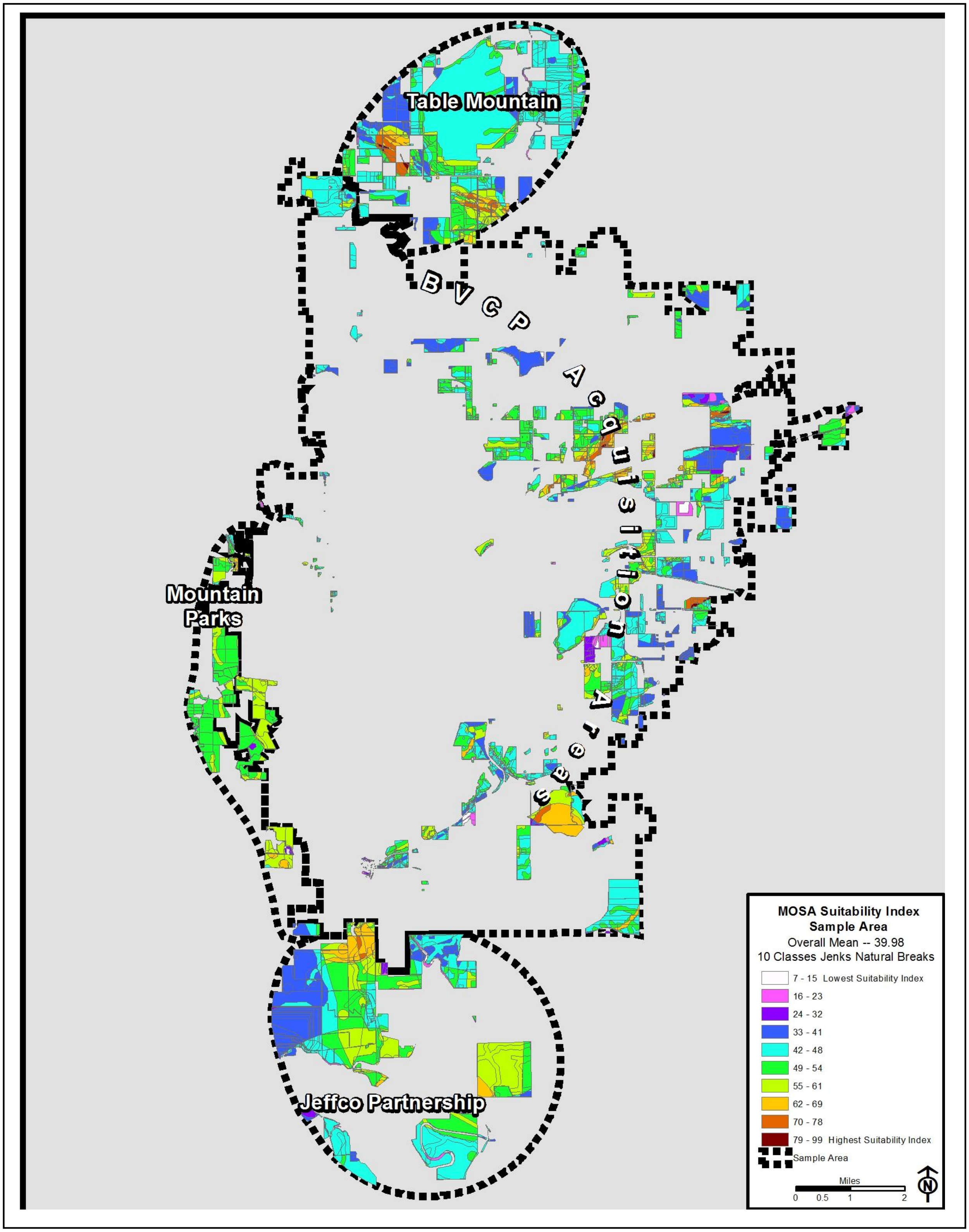
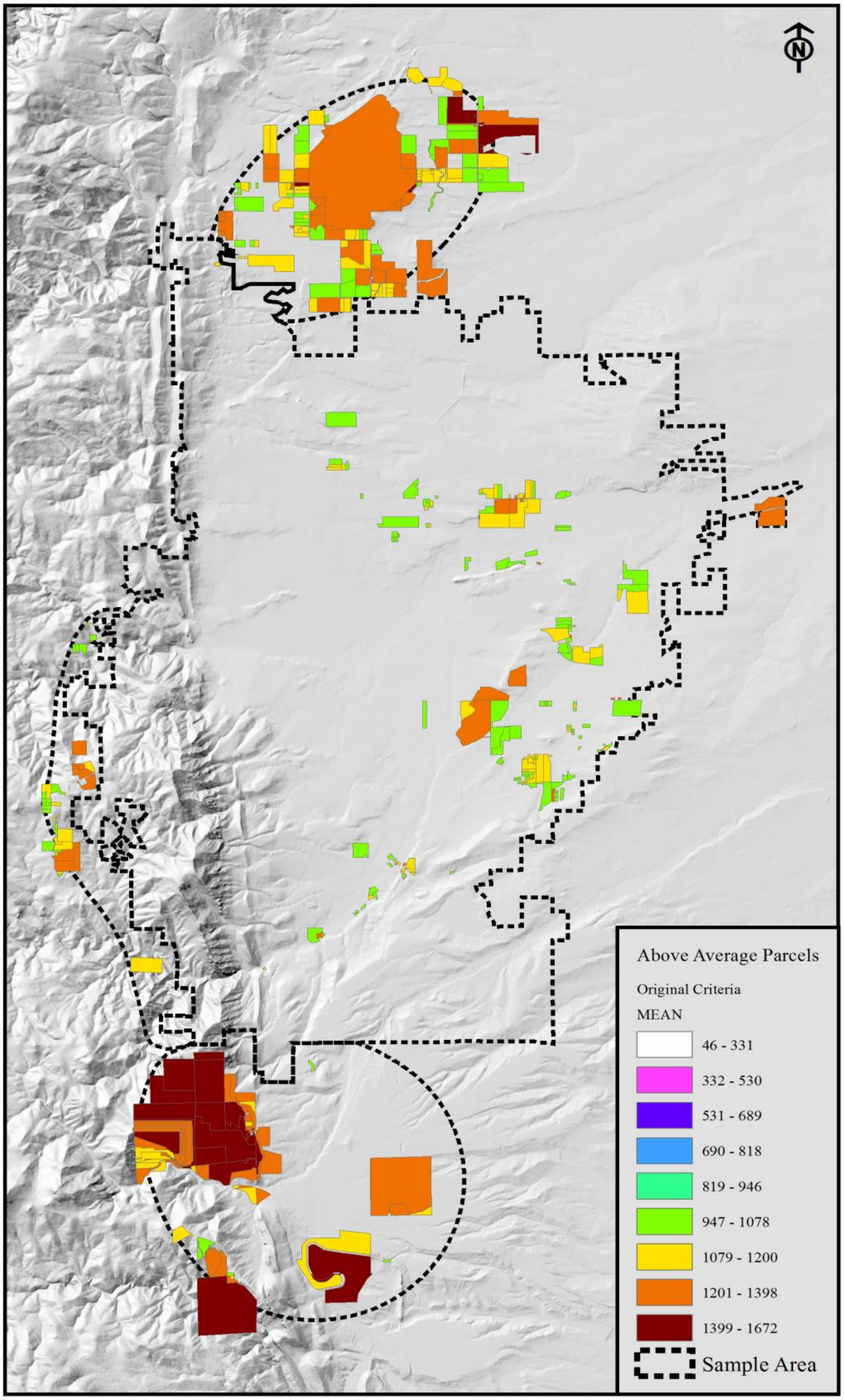
APPENDIX A: Weighted Criteria Analysis Using Jenks Classification Method on Pixels



APPENDIX B: ***Original*** **MOSA Parcels with Above Average Suitability Index**



APPENDIX C: ***Adjusted*** **MOSA Parcels with Above Average Suitability Index**