ONSHORE WIND POWER SYSTEMS (ONSWPS): A GIS-BASED

TOOL FOR PRELIMINARY SITE-SUITABILITY ANALYSIS

by

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ABBREVIATIONS AND ACRONYMS

AHP- Analytical Hierarchy Process

AWEA- American Wind Energy Association

CO_2- Carbon Dioxide

dB- Decibel (measure of sound pressure)

DOE- U.S. Department of Energy

DSS- Decision Support System(s)

EIA- U.S. Energy Information Administration

GHG- Greenhouse Gas(es)

GIS- Geographical Information System(s)

GW- Gigawatt (1 GW = 1,000 MW = 1,000,000,000 or 10^9 watts)

kW- Kilowatt (1 kW = 1,000 watts)

LCC- Land Class Code(s) (based on NLCD classifications)

m- Meter (the International System's unit of length)

m/s- Meters per second (the International System's unit for speed)

MC- Multi-Criteria

MCA- Multi-Criteria Analysis (also referred to as MC Analysis)

MCDM- Multi-Criteria Decision-Making

MCE- Multi-Criteria Evaluation

mph- Miles per hour (measure of speed)

MW- Megawatt (1 MW = 1,000 kW = 1,000,000 or 10^6 watts)

NAD_83- North American Datum of 1983 (geographic coordinate system)

NLCD- National Land Cover Database

NREL- National Renewable Energy Laboratory

NO_x - Nitrous Oxides

ONSWPS- On-Shore Wind Power System(s)

PTC- Production Tax Credit(s)

RES- Renewable Energy Source(s)

ROI- Return On Investment (economic measure)

RPS- Renewable Portfolio Standard(s)

SDSS- Spatial Decision Support System(s)

SMCA- Spatial Multi-Criteria Assessment(s)

SO_2- Sulfur Dioxide

STEM- Science, Technology, Engineering, and Math (education standard)

USGS- U.S. Geological Society

W- Watt (the International System's unit for power)

WECS- Wind Energy Conversion System

WPC- Wind Power Class(es)

WPS- Wind Power System(s)

WRA- Wind Resource Assessment

ABSTRACT

Wind energy was the fastest growing form of renewable energy in the world during the last decade and forecasts predict that this trend will continue. In the U.S., Renewable Portfolio Standards (RPS) and federal tax incentives drive this trend from a policy perspective, but despite its potential to reduce CO_2 emissions and dependence on foreign fuel for electricity generation, wind energy development remains a contentious issue and siting of wind power systems remains problematic. This thesis presents a GIS-based tool for preliminary site suitability analysis for Onshore Wind Power Systems (ONSWPS) that can be used to address these issues from a planning perspective. This tool incorporates Multi-Criteria Analysis (MCA) and the Analytical Hierarchy Process (AHP) along with various forms of spatial and sensitivity analysis to provide quick visual access to ONSWPS site selection information through a series of suitability maps.

CHAPTER 1: INTRODUCTION

1.1 Status of Wind Energy Development

Wind energy was the fastest growing form of renewable energy in the U.S. and the world during the last decade (Bohn & Lant, 2009; DeCarolis & Keith, 2006; Hoogwijk, de Vries, & Turkenburg, 2004; Rosenburg, 2008a; U.S. Department of Energy, 2008), and forecasts predict that this trend will continue for the next decade and beyond (U.S. Energy Information Administration, 2011). In the U.S., the majority of states have Renewable Portfolio Standards (RPS) in place that mandate a percentage of electricity generation from renewable energy sources (RES) (U.S. Energy Information Administration, 2011; Van Haaren & Fthenakis, 2011). In addition, several federal tax incentives drive the wind energy industry from a policy perspective (American Wind Energy Association [AWEA], 2008; Bohn & Lant, 2009; Rosenburg, 2008a). In fact, the growth of the wind energy industry is highly dependent on the existence of federal Production Tax Credits (PTC), which makes the cost of generating electricity from wind energy competitive with other forms of electricity generation (Bohn & Lant, 2009).

Despite its potential to reduce CO_2 emissions, conserve water and fuel, and reduce the country's dependence on foreign fuel for electricity generation, wind energy development remains a contentious social, economic, and environmental issue (DeCarolis & Keith, 2006; Denny & O'Malley, 2006; Kuvlevsky Jr., et al., 2007; Rosenburg, 2008b; Sutton & Tomich, 2005). The proper siting of wind power systems remains inherently problematic because geographical limitations, public opposition, wildlife conservation, electricity grid integration, and fuel market fluctuations all pose challenges for planners and developers.

Deciding which criteria to include in the site selection process, and how much priority to assign each criteria, is the subject of considerable research and public debate, but all agree that proper site evaluations and accurate resource assessments can save time, money, and resources and can help to mitigate causes of costly delays (Cavallaro & Ciraolo, 2005; Chen, Yu, & Khan, 2010; Dominguez & Amador, 2007; Hansen, 2005; Jankowski, 2009; Loring, 2007; Simao, Densham, & Haklay, 2009).

1.2 Research Statement

This thesis presents a GIS-based application for evaluating potential site suitability of Onshore Wind Power Systems (ONSWPS) in order to provide quick visual access to this information for politicians, developers, researchers, students, and the public. This application will be useful for preliminary site selection of utility-scale and large distributed wind power systems, and will be suitable for regional (approx. 1:3,000,000) and larger scale site suitability analysis based on a set of physical, economic, and environmental criteria, including topography, wind power capacity, land use, and proximity to infrastructure. This application can be integrated into Spatial Decision Support Systems (SDSS) as part of a Multi-Criteria Analysis (MCA) approach to ONSWPS siting, thus making it a valuable planning tool. Finally, as a demonstration of spatial problem solving, it can also serve as a teaching, learning, and decision-making tool through an interactive web-based interface and suitability maps.

The working hypothesis is that combining GIS spatial analysis and visualization capabilities with MCA is an effective approach for "solving" complex spatial problems like wind power system siting, which must balance numerous geographic, technical, environmental, economic, and social variables. The rationale is that this research can help ensure the best use of this form of renewable energy by making information more accessible to interested parties and by facilitating discussion on the aesthetic, environmental, and economic issues surrounding wind power development. The Middle Columbia River Basin, covering portions of Washington and Oregon States, was chosen as the pilot study region (Figure 1).

1.3 Motivation

The responsible production and use of energy is something that ties us all together as citizens of the world. Recent concern over the adverse effects of global climate change has spurred many nations to pursue alternative sources of energy (United Nations, 1997) and has set in motion numerous policies to integrate RES into existing national energy mixes at higher levels (Rosenburg, 2008a; U.S. Energy Information Administration, 2011). The creation of an economically viable renewable energy infrastructure is a monumental issue facing this and future generations, and contributions to research on this issue are of great value to decision makers, to society, and to me personally.

The primary motivation for my research is to develop a GIS-based tool that serves multiple practical purposes as well as integrates and expands on the work done by others in the RES siting field, with a particular focus on wind energy. The foundation of this project involved compiling, reviewing, and organizing the necessary data into a spatial database that supports site suitability analysis, as well as model development, sensitivity analysis, and the production of a series of site suitability maps.

Information dissemination is regarded as a critical factor in public acceptance of wind energy development, and this in turn has tremendous impacts on the successful implementation of wind energy projects (Berry, Higgs, Fry, & Langford, 2011; Bohn & Lant, 2009; Jobert, Laborgne, & Mimler, 2007; Loring, 2007; Malczewski, 2004; Rosenburg, 2008a; Simao, Densham, & Haklay, 2009; Sutton & Tomich, 2005; Van der Horst & Toke, 2010). By making this information more readily available to decision makers and the public, I hope to stimulate and enhance discussions on the subject of wind energy development, and by creating a tool that assesses many of the criteria involved in wind energy project siting I intend to provide a practical context for those discussions.

Wind energy is a rapidly growing industry in much of the U.S. and in the Pacific Northwest in particular. Washington State (where I live) has gone from having zero installed wind capacity in 2000 to ranking 6th nationwide in installed wind capacity, with 2,356 MW as of June 30, 2011. Oregon, which is 7^{th} nationally with 2,305 MW, has experienced nearly identical growth in that same period (U.S. Department of Energy, 2011). This trend is predicted to continue due to volatile fuel prices and socioeconomic pressure to move away from fossil fuel-based energy sources. Other incentives, such as the passage of Washington

State Initiative 937[1] in 2006, and generous federal, state, and regional subsidies for renewable energy projects, have also added to the momentum of this trend (North Carolina State University, 2011; U.S. Department of Energy, 2008). As the number of suitable sites is reduced through development, greater value will be placed on efficient methods to locate potential wind energy development sites (Kuvlevsky Jr., et al., 2007; Marinoni, 2004).

One important outcome of this thesis will be the ability to integrate this tool into Decision Support Systems (DSS), or more specifically, *Spatial Decision Support Systems* (SDSS). SDSS are used to address complex, multi-faceted spatial problems, such as land use planning and renewable energy siting, which require informed judgments rather than calculable solutions. Since the inception of computer-aided GIS, one of its primary uses has been land use planning; in fact, the evolution of GIS has largely been a response to the needs and techniques of land use planners and developers (Malczewski, 2004). The research and frameworkd presented here will draw on well-documented land use planning theory and research using GIS, and although it will rely on SDSS theory to inform some elements of its design, the primary focus will be on the GIS portion of this combination that can serve as a part of a SDSS for wind energy system siting.

Since RES siting is inherently multi-faceted, an approach capable of evaluating several criteria simultaneously must be used. GIS have the ability to assimilate, analyze, and visualize multiple spatial data sets that pertain to the different factors used for site selection, but GIS are limited in their ability to assign values to these factors. MCA has been

[1] State Initiative 937 mandates that large utilities (those that serve >25,000 people) obtain 15% of their energy from renewable resources by the year 2020.

shown to be an effective approach to assigning values to different criteria, and it is compatible with the functionality of GIS (Baban & Parry, 2001; Cavallaro & Ciraolo, 2005; Chen, Yu, & Khan, 2010; Conley, Bloomfield, St. George, Simek, & Langdon, 2010; Griffiths & Dushenko, 2011; Hansen, 2005; Janke, 2010; Jankowski, 1995; Lee, Chen, & Kang, 2009; Malczewski, 2004).

In fact, it is nearly impossible to find an RES siting study that does not use some form of MCA in combination with GIS. However, comprehensive review of these methods is lacking and I have not come across any examples of studies attempting to implement an existing methodology in another region. Additionally, the criteria evaluated in each study vary widely, so it is difficult to compare one methodology to another when the baseline datasets (i.e. input values) are different.

This thesis will examine and compare four of the MCA-GIS methods found in the literature before presenting a new framework, followed by some Sensitivity Analyses (SA). Comparing this methodology and model to those found in similar studies will provide insight into the reliability and effectiveness of these models for locating potential sites. Undertaking sensitivity analysis will provide some evaluation of the uncertainty involved in the MCA, which may help decision makers understand which criteria are more sensitive to subjective input values.

Another important outcome of this thesis will be the production and publication of multi-layered suitability maps using GIS. Such maps can be an effective means of assessing the suitability of potential sites for wind energy development because they can be a cost-effective and visually powerful information source (Griffiths & Dushenko, 2011; Hansen, 2005; Ramirez-Rosado, et al., 2008; Sidlar & Rinner, 2006; Simao, Densham, & Haklay, 2009). These maps can be displayed on the web to provide free, quick access for those interested in ONSWPS siting, and increasing access to this type of information has been shown to enhance public participation in the siting process (Berry, Higgs, Fry, & Langford, 2011; Sidlar & Rinner, 2006; Simao, Densham, & Haklay, 2009). It is beyond the scope of this thesis to explore the effectiveness of information dissemination on public participation, but based on the substantial body of research on this subject in the literature (Berry, Higgs, Fry, & Langford, 2011; Jankowksi & Nyerges, 2003; Jankowski, 2009; Jobert, Laborgne, & Mimler, 2007; Sidlar & Rinner, 2006; Sieber, 2006; Simao, Densham, & Haklay, 2009; Van der Horst & Toke, 2010), I believe it is reasonable to work from the assumption that increasing the availability of information will benefit public participation in the process.

CHAPTER TWO: BACKGROUND

2.1 Why wind energy?

Onshore wind power has tremendous potential as a competitively-priced alternative to fossil fuel-based sources of electricity generation (Conley, Bloomfield, St. George, Simek, & Langdon, 2010; Elliott, Wendell, & Gower, 1991; U.S. Department of Energy, 2008; U.S. Energy Information Administration, 2011), and it is the fastest growing form of renewable energy in the U.S. since 2000 (Bohn & Lant, 2009; Hoogwijk, de Vries, & Turkenburg, 2004; Rosenburg, 2008a). Although it currently comprises less than 1% of the present energy supply (Rosenburg, 2008a), researchers estimate that wind energy could be the source of 20% of the U.S. electricity supply (American Wind Energy Association [AWEA], 2008; U.S. Department of Energy, 2008).

In addition, wind energy development has potential environmental, economic, and energy security benefits over fossil fuel-based sources, including the potential reduction of CO_2 and other greenhouse gases (GHG), the reduction of air pollutants (SO_2, NO_x, etc.) and other toxins, water conservation, domestic job creation, landowner revenue generation and rural tax revenue, and perhaps most importantly, reduced reliance on foreign sources of fuel for electricity generation (American Wind Energy Association [AWEA], 2008; DeCarolis & Keith, 2006; Denny & O'Malley, 2006; Rosenburg, 2008a).

2.2 Basics of wind energy

Wind energy is a form of solar energy and, like solar, wind is an intermittent, or variable output, source of energy (Ibrahim, Ghandour, Dimitrova, & Perron, 2011; Rosenburg, 2008a). Wind turbines, typically of a horizontal-axis configuration[2], capture the kinetic energy in the wind with propeller blades and convert it to other forms of useable energy (American Wind Energy Association [AWEA], 2004). The current trend is to convert this energy into electricity which can be used to supplement or replace the electricity traditionally created from fossil fuels[3] (Denholm, Kulcinski, & Holloway, 2005; Ibrahim, Ghandour, Dimitrova, & Perron, 2011; Rosenburg, 2008a). Because of this conversion process, all wind energy systems technically should be called *wind energy conversion systems* (WECS) (Billinton & Gao, 2008), but his thesis will use the nomenclature *wind power systems* (WPS)- and specifically *onshore wind power systems* (ONSWPS) - in order to avoid confusion between the entire power system and the on-site energy conversion part of the system.

Further, a wind power system can consist of one single turbine or hundreds of turbines, ranging from small distributed systems to large distributed systems to utility-scale systems, and the term *wind farm* is often used interchangeably in the literature. However, generally speaking, wind farms do not include small distributed systems, such as a single home-owner or a rural school, because the energy is only used on site and is not connected to the grid. Because of the wind resource dataset used in this thesis (at 50 m above the

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[2] See Dabiri (2011) for a discussion of horizontal- and vertical-axis configurations.

[3] Some argue that wind energy is a better candidate for hydrogen production to be used in fuel cells, see (Granovskii, Dincer, & Rosen, 2007).

ground), the appropriate focus will be on large distributed systems and utility-scale systems, and the term wind farm will sometimes be used to describe these systems, particularly when discussing other studies that use the term.

An understanding of the complete power system is necessary for thorough site suitability analysis, including the energy conversion and storage systems, turbine type and arrangement, power transmission, grid integration, load balancing, and the wind resource itself. While these factors must be addressed at some point in the site selection process, they primarily affect the final cost of the system or other economic measurements such as return on investment (ROI). Detailed assessments are expensive and these expenses are only appropriately incurred by developers in the later stages of a project. This thesis focuses on preliminary site selection using a GIS-based tool, and as such will make many informed assumptions about these economic factors based on the literature and use proxy values where appropriate.

2.3 Onshore vs. Offshore Wind Energy Development

There is a notable dichotomy between onshore and offshore wind energy development in terms of project costs, environmental impacts, public opposition, infrastructure development, and siting constraints that essentially makes them two different forms of renewable energy. The spatial datasets required for onshore wind energy assessments will not suffice for offshore and vice versa, and the economic assessments of each are limited to their respective forms. For example, according to the U.S. Energy Information Administration (2011), the national average levelized cost of onshore wind energy is approximately 39% the cost of offshore wind energy, and this disparity impacts the economic arguments for wind energy development significantly. Due to the various discrepancies between onshore and offshore wind energy development and the different datasets that would be required to model the two, this thesis will be limited to onshore wind energy analysis, which currently is cost-competitive with other forms of electricity generation[4].

2.4 Renewable Energy Source (RES) siting

RES availability is always a matter of geography, and the first step in the siting process must always be an assessment of the availability of a resource at a given location (Dominguez & Amador, 2007; Malczewski, 2004; Voivontas, Assimacopoulos, Mourelatos, & Corominas, 1998). For wind energy, this consists of assessing and measuring wind characteristics like speed, power, density, prevailing direction, daily and seasonal variation, long-term consistency (climate cycles), turbulence and wake, temperature, and uncertainty of the wind at various heights[5] above the Earth's surface (American Wind Energy Association [AWEA], 2004; Dabiri, 2011; Ozerdem, Ozer and Tosun, 2006; Prasad, Bansal and Sauturaga, 2009). This type of analysis is called a Wind Resource Assessment (WRA) and it is critical to any wind energy project (Prasad, Bansal, & Sauturaga, 2009).

However, different scales and applications of wind energy development require WRA at different hub heights (Elliott, Wendell, & Gower, 1991). For example, small distributed

[4] With the federal Production Tax Credit in place, see Bohn & Lant (2009).

[5] Typically called hub heights, referring to the central point along the blade axes where the "hub" of the turbine generator is located (American Wind Energy Association [AWEA], 2004).

systems typically do not need to know how the wind behaves 80 meters above the ground because their turbines will not be that tall, whereas large utility-scale wind operations would be acutely interested in that information. It is not within the scope of this thesis to make detailed WRA or to critique the methods used to make WRA; it is an extremely technical, time- and resource-intensive process and, fortunately, much work has already been done for this type of application.

Organizations around the world have dedicated substantial resources to measuring the wind at different hub heights so that planners, developers, and the public have access to this information. The National Renewable Energy Laboratory (NREL) is one such organization in the U.S., and they have compiled a number of useful datasets for utility-scale or large distributed wind energy development (Janke, 2010). This thesis utilizes the NREL High Resolution Wind Resource at 50 m dataset for the Pacific Northwest Region of the U.S., which can be obtained at http://www.nrel.gov/gis/data_wind.html. This dataset provides an adequate level of detail for regional analysis of annual average wind power based on wind power classes (WPC) at a height that is useful for utility-scale and large distributed systems, and it is a quintessential starting point for wind energy site selection processes in the U.S.

2.5 Decision Support Systems (DSS) and Geographic Information Systems (GIS)

DSS are often combined with GIS to address problems that are inherently spatial or have a geographic component, yielding Spatial Decision Support Systems (SDSS) (Marinoni, 2004). GIS alone do not constitute SDSS because a GIS just handles the data; it does not provide a systematic approach to making complex, subjective decisions. Conversely, SDSS do not have the all of tools required to unlock the value in complicated spatial data, and so combining the two is necessary when seeking solutions to multi-faceted spatial problems (Jankowksi & Nyerges, 2003; Malczewski, 2004; Simao, Densham, & Haklay, 2009).

The research and tool presented in this thesis can be used as part of SDSS for locating potential, suitable, and optimal sites for wind energy development, the expansion of which is a governmental and societal goal (American Wind Energy Association [AWEA], 2008; Bohn & Lant, 2009; Hoogwijk, de Vries, & Turkenburg, 2004; Rosenburg, 2008a; U.S. Department of Energy, 2008; United Nations, 1997; Van Haaren & Fthenakis, 2011). DSS are a common method for land-use planning and project management activities that require the consideration and analysis of multiple, often diverse or unquantifiable, variables (Baban & Parry, 2000; Cavallaro & Ciraolo, 2005; Jankowksi & Nyerges, 2003; Malczewski, 2004; Ramirez-Rosado et al., 2008; Simao, Densham, & Haklay, 2009). Decision makers employ DSS when making complex decisions that involve many stakeholders, often with conflicting priorities and agendas, and the result is nearly always a compromise rather than a unanimous decision (Cavallaro & Ciraolo, 2005).

GIS offer a level of functionality that is difficult to achieve with other software packages; they have powerful analytic capabilities, exceptional spatial data management, storage, and retrieval functionality, and an array of visualization tools that make them an invaluable tool for site suitability analysis (Malczewski, 2004; Marinoni, 2004). Modern GIS have the advantage of using computers, but the spatial analysis techniques used in land-use planning and renewable energy siting are not new (Malczewski, 2004; Rosenburg, 2008b). Hand-drawn maps using overlay techniques for land use planning purposes date to the late 19th and early 20th centuries (Malczewski, 2004). As technology has evolved, the use of GIS has spread to nearly all sectors of society, and although there are concerns over the equity offered by this highly technical software (Sieber, 2006), the body of scientific research supports the notion that GIS is an effective way to approach site suitability problems (Baban & Parry, 2000; Cavallaro & Ciraolo, 2005; Dominguez & Amador, 2007; Griffiths & Dushenko, 2011; Hansen, 2005; Janke, 2010; Malczewski, 2004; Rosenburg, 2008b; Sidlar & Rinner, 2006; Simao, Densham, & Haklay, 2009; Tegou, Polatidis, & Haralambopoulos, 2010; Van Haaren & Fthenakis, 2011).

2.6 Multi-Criteria Analysis (MCA)

Multi-Criteria Analysis (MCA) is a method for evaluating the relative importance of multiple variables as input criteria for making complex decisions (Chen, Yu, & Khan, 2010; Hansen, 2005; Marinoni, 2004; Van Haaren & Fthenakis, 2011). MCA is by nature a complex process, the essential concept being that a number of relevant criteria must be identified and assessed in terms of value, or weight, with respect to the influence the criteria have on the final decision. In spatial analysis, this is often accomplished by creating a suitability map that is composed of several layers, each layer representing one of the criteria. The criteria are given a weighted suitability score, and these scores are represented as different classes or categories, which are then symbolized on the map layer showing the suitable areas for that criteria. The layers are then overlaid on the map to yield a final site suitability map, from which the user can then identify optimal areas and continue with a more detailed investigation of those sites.

This method is noteworthy for its situational-adaptive properties and ability to assess a wide range of tangible and intangible variables based on an assigned weighting scheme rather than as hardened values. Variations of MCA pervade the literature[6], but they all rely on some sort of weighting scheme and they all share the common goal of providing a framework to assess many disparate types of criteria (Baban & Parry, 2000; Berry, Higgs, Fry, & Langford, 2011; Cavallaro & Ciraolo, 2005; Chen, Yu, & Khan, 2010; Conley, Bloomfield, St. George, Simek, & Langdon, 2010; Griffiths & Dushenko, 2011; Hansen, 2005; Janke, 2010; Malzcewski, 2004; Simao, Densham, & Haklay, 2009: Tegou, Polatidis, & Haralambopoulos, 2010; Van Haaren & Fthenakis, 2011). In the case of wind energy siting, these include avian mortality, land use/land cover/land ownership, wildlife habitat, wind speed/wind power/wind density estimates, energy storage and energy grid requirements, visual and auditory disturbances, topography, geology, radar interference, public participation, and cost-revenue analysis. This thesis will not include all of these criteria because high quality data is either not available or is too location-specific for regional analysis, and the intent is to create a tool that can be used for preliminary site selection based largely on geographical criteria.

[6] Other variations include: MCE (Multi-Criteria Evaluation), MCDM (Multi-Criteria Decision-Making), MCDSS (Multi-Criteria Decision Support Systems), SMCDM (Spatial Multi-Criteria Decision-Making), and SMCA (Spatial Multi-Criteria Analysis).

Most of the relevant criteria for preliminary analysis can be addressed using just a few data layers because multiple constraints can often be satisfied by running different spatial analysis operations on the same GIS layer. For example, noise, visual disturbance, and safety (from parts malfunctions or ice throws) are all criteria that can be analyzed from buffering a 'major cities/urban areas' layer, and this same layer also embodies an economic argument, as an urban area represents a demand for electricity. There are nonetheless some criteria that require multiple data layers, such as the critical habitat criterion, which assimilates information from several departments and organizations (i.e. U.S. Department of Fish and Wildlife, Bureau of Land Management, U.S. Department of Ecology, Nature Conservancy, etc.), and so will have several input layers.

Because criteria weights are based on the perceived importance of the selected criteria (in which the selection process itself is most likely biased) to the different actors, little consensus exists on how to derive MCA criteria weights. One party may argue that protecting avian habitat should hold more weight than protecting rural homeowners from ”shadow flicker” (the moving or flickering shadows cast by rotating turbine blades, often rapidly) or turbine noise, while another may consider avian mortality to be a negligible issue and cite the evidence that cars kill more birds than turbines each year. Another may consider turbines a blight on the landscape that will reduce tourist dollars while another may consider turbines a valuable source of income (wind power developers often lease agricultural land from rural landowners), while others may even consider them a tourist attraction. The bottom line is that with so many actors involved and so many agendas to reconcile, wind energy development is always a compromise.

One of the most common methods for deriving criteria weights is by using the Analytical Hierarchy Process (AHP). Originally described by Saaty (1977), this rule-based method is one of the most commonly used by decision-makers and planners for evaluating multi-criteria decisions (Pohekar & Ramachandran, 2004), and it provides a calculable consistency factor (in the form of a ratio) that provides decision-makers with a considerably higher level of confidence in the criteria weighting process (Boroushaki & Malczewski, 2008; Chen, Yu, & Khan, 2010; Saaty, 1977).

2.7 Critical Factors in Wind Energy Siting

Besides the wind resource itself, there are a number of environmental and economic criteria that limit the suitable areas for wind energy development. After a thorough review of the literature, six dynamic criteria have been identified in this analysis as critical: wind power class (WPC), distance to the electricity grid, distance to cities/urban areas, distance to roads, land cover class, and slope. Other criteria identified in this analysis as important to wind energy development include critical wildlife/vegetation habitat, areas near airports, military installations, National Parks, Forests, Recreation Areas, and Monuments, state and local parks or recreation areas, wetlands, tribal lands, and areas with karst or unstable soil conditions.

These criteria are classified numerous ways in the literature, but this thesis will focus on separating them into two basic categories: *simple* and *dynamic*. Simple criteria are evaluated in Stage 1 of this analysis, the dynamic criteria are evaluated in Stage 2, and the two are combined in Stage 3. The sensitivity analysis (SA) will evaluate only the dynamic (or weighted) criteria.

In this thesis, the defining property of critical criteria is that they are dynamic. These criteria are dynamic in the sense that their impact on the suitability of a particular site changes in relation to the other criteria depending on the perceived importance (or weight) of the criteria. They are also more difficult to quantify because they deal with a range of values. As such, these criteria must be evaluated differently than the simple criteria, which can be evaluated with simple Boolean-type exclusionary process based on geographical constraints. The simple criteria represent areas that are generally not suitable for development under any circumstances, and these areas are excluded from the analysis in Stage 1. Many of these criteria relate to ecological constraints and habitat preservation, especially for avian (birds, bats, etc.) species, which are the most adversely affected by large wind turbines (Barrios & Rodriguez, 2004; Kuvlevsky Jr., et al., 2007; Madders & Whitfield, 2006; Sutton & Tomich, 2005).

2.8 Sensitivity Analysis (SA)

SA is a beneficial measure to include in MCA approaches because it provides insight into the sensitivity of the outputs (i.e. the suitable areas for development) to errors, inaccurate assumptions, or perturbations in the input values (i.e. the criteria values and/or criteria weights). SA aids in assessing the precision and limitations of the model (Chen, Yu, & Khan, 2010). Because the criteria values are based on the perceptions of various stakeholders and decision makers, they are often subjective or conditional. The criteria weights may also be subjective or conditional, even if using a systematic approach such as AHP to derive criteria weights (Marinoni, 2004; Saaty, 2004), or they may represent a range of values (Boroushaki & Malczewski, 2008; Chen, Yu, & Khan, 2010; Karapetrovic & Rosenbloom, 1999). SA can therefore help identify where the greatest uncertainty exists, whether in criteria values or criteria weights, and can identify which criteria need to be evaluated more carefully.

2.9 Visualization

One of the greatest advantages of GIS is visualization. Most researchers using GIS-based approaches to RES siting use maps to visually analyze locations and display results. Although recent work has explored presenting 3D visualizations via virtual reality technology (Bishop & Stock, 2010; Stock, et al., 2008) that show what a site would look like after development (i.e. with wind turbines, new roads, power lines, etc.) as a way to evaluate public acceptance of new projects, or even through the use of video games (Bishop, 2011), maps remain the predominant visualization medium. Different types of maps and mapping applications have been used: dynamic maps, web-based maps, static maps, argumentation maps, and suitability maps (Conley, Bloomfield, St. George, Simek, & Langdon, 2010; Elliott, Wendell, & Gower, 1991; Rodman & Meentemeyer, 2006; Sidlar & Rinner, 2006; Simao, Densham, & Haklay, 2009). Maps can be extremely effective as a vehicle for communicating geographic information and will be an invaluable part of the effectiveness of this thesis in achieving its outcome of increased information dissemination.

2.10 Study Area

The geographic study area for this thesis is limited by the number of the geographic data layers, the size of the datasets, and the computational time required to perform the required analysis. Under these constraints, a 270 by 270-mile area (72,900 sq. miles or approximately 45.8 million acres) was chosen to facilitate regional analysis at a scale of 1:3,000,000 and larger (NAD_83 Geographic Coordinate System, Oregon Statewide Lambert Conformal Conic projection). The chosen area encompasses the Middle Columbia River Basin, which comprises the southern portion of Washington State and northern portion of Oregon, east of the Cascade Mountain Range (Figure 1). The approximate study area range is 123° W to 117° W and 44° N to 48° N.

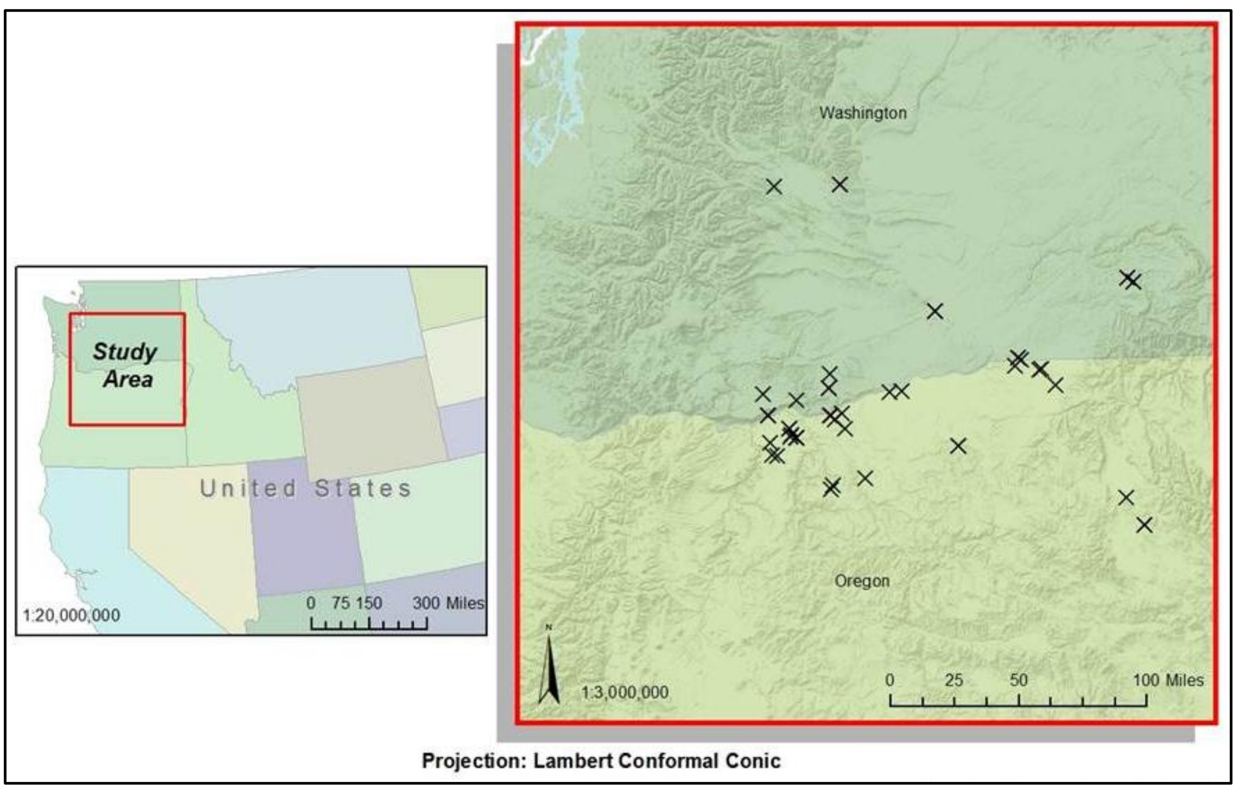

Figure 1: Map showing thesis study area and the locations of existing onshore wind farms (black 'X' symbols in map to the right).

This area was selected for analysis for two reasons: 1) All of the existing (and planned) onshore wind farms in Washington and Oregon are located in this region, indicating that this is a viable area to apply this tool to, rather than randomly selecting an area where there may be no suitable sites. If this tool shows promise in this study area, examination of other areas would then be justified, and; 2) The inclusion of an "existing wind farms" GIS layer allows us to evaluate the models and the criteria weights in a pragmatic, rather than scientific, way. Since wind farm siting is not, as of yet, a purely scientific endeavor, having so many unquantifiable variables and containing enormous uncertainty in regards to the social and economic variables, a simple comparison with where wind farms actually exist may provide additional insight into the effectiveness and limits of the models. If a study area was chosen where no wind farms existed, this type of "ground truth" evaluation would be impossible.

CHAPTER THREE: METHODS AND MATERIALS

3.1 Project workflow

MCA-GIS site suitability projects often have similar workflows, and this thesis follows a basic approach, beginning with a detailed literature and methods review and the careful selection of the criteria to by analyzed (Figure 2). This first step is critical in the outcome of the project. A number of routine GIS processes and operations are then performed to generate the dataset, followed by the spatial analysis portion of the project, including sensitivity analysis, and finally the output maps are created and published.

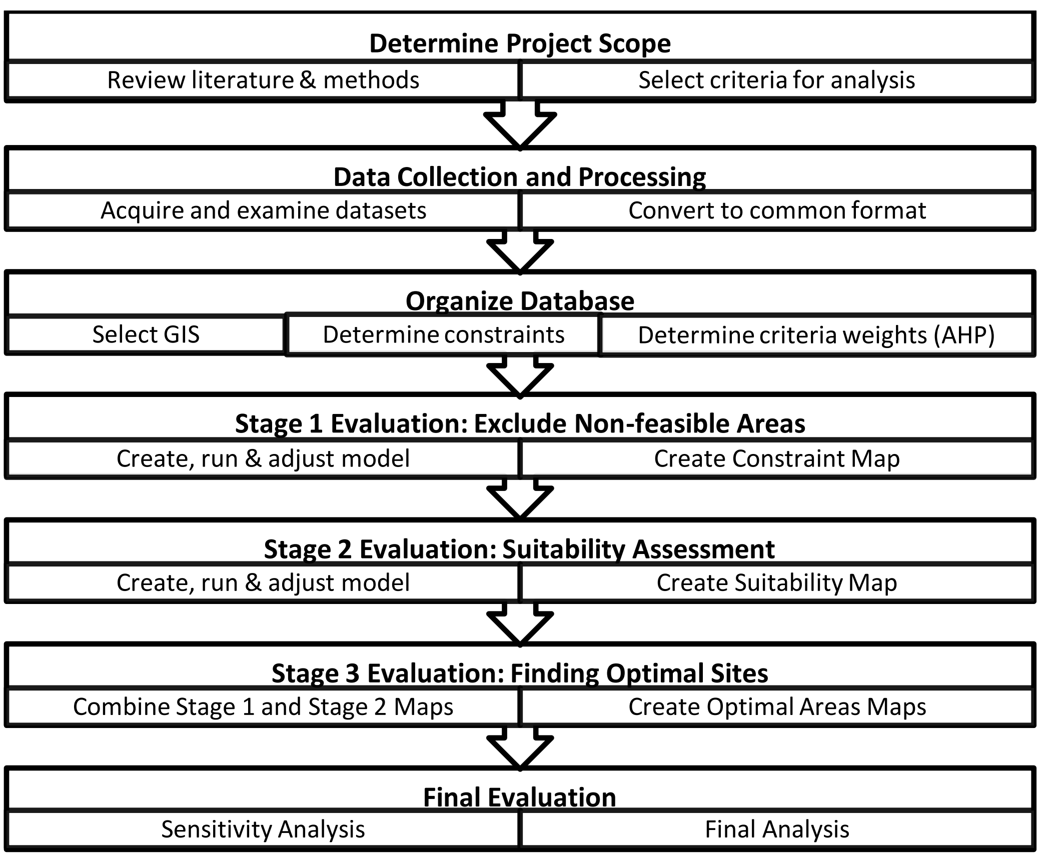

Figure 2: Schematic showing project workflow.

3.2 MCA Methodology Comparison

This thesis reviews four MCA/GIS-based studies for wind farm site suitability prior to presenting its own framework. These studies were selected based on the similarities of their geographic study areas in terms of the level of infrastructure development, development costs and standards, social attitudes, the geographic features, and the policies and political objectives. It is difficult, for example, to compare a site selection study performed in a developing country having an unstable political structure with a study performed in New York State because the perceived values of the various economic and environmental constraints may vary widely, and, of course, policies at the federal, regional, state, and/or local level can have a tremendous impact on development potential. Specific policies aside, these four studies compare relatively well and all contribute something valuable to the framework presented in this thesis.

Study A

The first approach was applied in the U.K. by Baban and Parry (2001) using the IDRISI GIS. Fourteen constraints were evaluated (see Table 1 at end of section), but there were some notable exclusions: airports, military facilities, unstable soil conditions, national parks and forests, or any specific mention of critical avian habitat or migratory zones. The authors selected the constraints based on results from questionnaires sent out to local council bodies and private wind companies, who referred to guidance documents about wind farm siting, and so there is no argument against the relevance of these criteria for that region. However, based on the literature it seems that the excluded constraints are also critical to consider, and the lack of a detailed description about the ecological constraints data is somewhat unsettling.

Baban and Parry applied a three-part approach to their analysis. The first stage was to exclude unsuitable sites (cell scores of 10 = total constraint; 0 = no constraint), and this was followed by a comparative analysis of two weighting schemes. The first scheme assumed that all criteria weights were equal, while the second assigned weights based on their perceived importance. The authors grouped the factors into four classes of importance prior to entering the layers into pairwise comparisons, from which the relative importance of each layer was compared to the others, ultimately yielding a pairwise matrix of all layers. From this matrix, the principal eigenvector could be computed to determine a best-fit set of weights for the criteria.

However, it is unclear what process the authors used to determine which factors fell into which classes, and thus it is difficult to interpret the results in a practical way, and this lack of measurable consistency in the selection process limits the effectiveness of the methodology. For example, Grade-1 factors included slope, roads, and urban centers, while "ecological sites" and water bodies (which were the authors' proxies for critical wildlife habitat) were listed as Grade-2 factors, and there was no mention of distance to the electrical grid or the wind resource itself in this section (these were listed as constraints earlier in the article however). While the pairwise matrix method may be sound, the input values seem to have been arbitrarily selected, and, if questioned by planners or conservationists, the authors of this study may have a difficult time defending their results.

The most important conclusion from this study was that using a variable weighting scheme (derived from calculating the principal eigenvector of the pairwise matrix) provided a more effective method for identifying more suitable land area than simply assuming equal weights for all layers. This makes sense because giving equal weight to a secondary or tertiary criterion will most likely either exclude more land area or lower the suitability scores of more land area than it should. It could also reduce the suitability scores for the most important criteria, further reducing the area of land scored as most suitable. This is a basic form of sensitivity analysis (SA), but there remains a high degree of ambiguity due to the synergistic qualities of complex, multi-criteria datasets.

Study B

The second approach was used in the Greater San Francisco Bay Area of California by Rodman and Meentemeyer (2006). The study area is heavily populated and has severe geographic constraints, which present a considerable challenge for wind development. The authors employed a four-part analytic framework, first calculating suitability scores for a physical model, an environmental model, and a human impact model, and then ran a series of combined models among all three, averaging the scores. Much like the first study, if any location had a suitability score of '0' (Unsuitable = 0; Excellent = 4) in any of the single models, then that location would receive a score of '0' in the combined model as well, no matter what the score was in another model. The models were run for both small-scale (>4.5 m/s), grid connected turbines and large-scale (>7 m/s) turbines.

Rodman and Meentemeyer (2006) did a better job explaining the rationale behind their weighting scheme, although we see a fascinating example of conflicting perceptions of importance between this study and Baban and Parry (2001). In their environmental model, the Rodman and Meentemeyer (2006) assigned the highest weight to land use/vegetation, and within that category cropland and pasture scored the highest for suitability because farmers and ranchers can earn extra income by leasing their land to wind developers and it does not significantly disrupt farming activities or disturb undeveloped land. Conversely, Baban and Parry (2001) included a specific constraint against taking up Grade-1 or Grade-2 agricultural land, thus demonstrating the problems inherent in assigning weights based on subjective perceptions. This is also an example of the complexity added through economic arguments, which are extremely context-dependent and therefore difficult to assess and model at the preliminary stage.

The advantage of this approach is that it allows for some basic SA among the three models. The physical model provides the land area where development could feasibly occur, while the environmental and human impact models reduce that land area through a set of constraints that can quantifiably indicate which criteria have the most impact on the suitable land area. However, as with the first study, there are some notable exclusions: proximity to the electricity grid and visual disturbance (proximity to urban areas and recreation areas), to which the authors admit, but also proximity to roads, water bodies, military installations, airports, tribal lands, critical avian habitat, and unstable soil conditions (karst).

Although the authors used a relatively sparse criteria set, their results show that their models accurately located three land areas where wind development had already occurred or had been planned. However, they admit that public opposition was present at two of the three sites – one site in particular where public opposition prevented development altogether – and they suggest that their models could benefit from more detailed datasets and the inclusion of a public acceptance factor.

Study C

A third approach, by Van Haaren and Fthnakis (2011), was conducted for New York State using ArcGIS 9.3.1 and it employed a three-stage framework: Stage 1 entailed the exclusion of non-feasible sites, Stage 2 consisted of an economic evaluation, and Stage 3 was a bird impact evaluation. This study is the most involved in terms of evaluating the economic arguments and constraints, and is atypical among wind farm site suitability studies because it looks at an entire (relatively large) state rather than a small geographic study area. The authors use the term spatial multi-criteria assessment (SMCA) to describe their approach.

The authors went into great detail to describe their rationale behind the selected criteria, and they drew on a more comprehensive dataset than the first two studies. In addition to the expanded dataset and economic evaluation, other unique facets of this study are the inclusion of geologically unstable areas (specifically karst, which results in porous grounds, sinkholes, and caves)[7], the exclusion of important bird areas (IBA), land clearance costs, and a measure of cost optimization between building new substations and

[7] For a detailed discussion of karst geology, see Waltham & Fookes (2003).

upgrading/expanding existing facilities. After the exclusion of non-feasible sites (Stage 1), the authors ranked the remaining areas by net present value (NPV) based on the cost for adding feeder lines, the cost for building new roads, and the cost of land clearing.

While the addition of an economic evaluation is helpful, it is a bit problematic because the costs of the technology, the behavior of the wind resource, and the costs of producing wind energy are not constant, and also wind energy development is largely policy-driven at the regional, state, or local level (Boccard, 2009; Bohn & Lant, 2009; Ibrahim, Ghandour, Dimitrova, & Perron, 2011). This is not to say that calculating the NPV of selected areas is a meaningless exercise; it is certainly a valuable measure to developers and planners and so must be considered at some stage in the planning process. The problem is the inherent limitation of calculating the NPV at such a scale (an entire state) based on one turbine type and its associated nameplate value (the maximum output rating of a turbine). Studies have shown that the nameplate capacity estimates are often significantly less than the realized values (Boccard, 2009), and this must be taken into consideration in any detailed economic evaluation. In the author's defense, they do admit the limitations of this type of assessment and suggest that the user of the tool can change these input values to suit the situation, which is an advantage of this model.

Another important feature of this study was the inclusion of criteria specifically focused on avian habitat. Bird and bat mortality from turbines and habitat disturbance or destruction are among the most controversial issues surrounding wind energy development (Barrios & Rodriguez, 2004; Conley, Bloomfield, St. George, Simek, & Langdon, 2010; Kuvlevsky Jr., et al., 2007; Sutton & Tomich, 2005), but this was the only study reviewed here that included this constraint.

The results of this analysis were compared to the locations of existing wind farms in NYS and the tool accurately predicted feasible sites for each existing wind farm, although they were not always located in the most suitable areas. One important conclusion from this study is that the MCA-GIS method is effective in identifying suitable areas for development. However, the study was weakened by the absence of any robust sensitivity analysis, particularly regarding the economic criteria.

Study D

The final study reviewed here, by Tegou et al. (2010) for the Island of Lesvos, Greece, takes the MCA-GIS methodology a step further by including a systematic approach to selecting criteria weights using the AHP. The AHP allows the user to assign criteria weights based on relative importance (pairwise comparisons) to the overall goal of the decision hierarchy, rather than based on perceived importance. The result of the pairwise comparisons for all criteria is a pairwise matrix from which the principal eigenvector can be calculated. Although Baban and Parry (2001) employed the pairwise comparison portion of this method, they did not mention the use of any systematic method (such as the AHP) to classify their criteria into grades of importance, and so were unable to evaluate the consistency of their judgments.

Consistency is crucial to multi-criteria decision making because of the complexity of the criteria weighting process and the likelihood of bias (either intentional or unintentional) on the part of the different decision-makers (Chen, Yu, & Khan, 2010). An improved consistency statistic does not necessarily mean that the judgments will lead to the best answer in regards to the "real world" objective, but it does mean that the judgments are significantly different from random (Saaty, 1977). Tegou et al. (2010) included two measures of consistency in their approach: a consistency index (***CI***) and a consistency ratio (***CR***). The *CI* can be measured by the formula (Saaty, 1977):

$$CI = \frac{\lambda_{\max} - n}{n-1} \tag{1}$$

where $\boldsymbol{\lambda_{max}}$ is the largest eigenvalue in the matrix and reciprocal matrix and $\boldsymbol{n}$ is the number of criteria. If there are no inconsistencies in the pairwise comparisons, then $\lambda_{max} = n$. The CR measures coherence of the pairwise comparisons, written as:

$$CR = \frac{CI}{RI} \tag{2}$$

where ***RI*** is the mean *CI* of a set of randomly generated comparison values (Saaty, 1977), and generally a *CR* value greater than 10% indicates significant inconsistency and suggests that the user reevaluate their judgments of relative importance regarding the criteria (Tegou, Polatidis, & Haralambopoulos, 2010).

Another important aspect of this methodology is the inclusion of sensitivity analysis. The authors used a technique similar to that of Baban and Parry (2001), but included four weighting scenarios instead of two. The first assumed that all criteria have equal weights, the second scenario set the "visual impact" criterion to zero, the third scenario set the environmental criteria to zero, and the fourth set the economic criteria to zero. The results show that the land area considered most suitable (scores of 0.9-1.0) was still relatively small in all cases, but the important conclusion by Tegou et al. (2010) was that "each selected criterion is influential in the evaluation of the study region."

Their conclusion seems like a gross generalization, but it tells us two valuable things: 1) the inclusion or exclusion of any relevant criterion is critical to the analysis, and so the set of evaluated input criteria may impact the analysis just as much, if not more, than the analysis method itself, and; 2) the relationship amongst the criteria is complex and dynamic, so the measurement of consistency in the criteria weighting assignment is crucial.

3.3 MCA Comparison Discussion

This review has tried to present the selected studies in a way that illuminates the advantages and shortfalls of each as well as shows a progression of methodologies. This thesis draws on the conclusions from the studies reviewed here in formulating its framework, and so much of the theory behind the analysis used in this framework is built on the ideas seen in these four studies, namely: 1) the use of pairwise comparisons and a pairwise matrix and the calculation of the principal eigenvalue; 2) the use of the AHP to assign criteria weights; 3) the use of a GIS grid format (raster) and the weighted overlay tool; 4) the use of a three-part analysis approach, beginning with the exclusion of infeasible sites; and 5) the use of a more comprehensive dataset based on a combination of the layers used in these four studies. A summary table is provided below for comparative purposes.

Table 1: Summary of relevant input criteria for four wind farm siting studies.

	Criteria/Constraint	***Baban & Parry***	***Rodman & Meentemeyer***	***Van Haaren & Fthnakis***	***Tegou et al.***
1	Proximity to Roads	x		x	x
2	Proximity to Urban Areas/Cities	x	x	x	x
3	Proximity to Electrical Grid	x		x	x
4	Proximity to Water Bodies	x		x	x
5	Proximity to Forested Land	x	x		x
6	Proximity to Historic Sites	x			x
7	National Parks, Forests, and Monuments	x (National Trust Property only)	x (public parks only)	x	
8	Military Installations			x	
9	Airports			x	x
10	Tribal Land			x	
11	Wind Speed/Wind Power Class	x	x	x	x
12	Slope	x	x	x	x
13	Aspect (Orientation)	x			
14	Critical Avian Habitat			x	
15	Critical Habitat/Conservation Areas	x (“ecological sites”)	x (endangered species present? Y/N)	x	x
16	Soil Type (Karst)			x	
17	Land Use Type	x	x		x
18	Wetlands			x	x
19	Electricity Demand	x		x	x

3.4 Proposed Framework

As illustrated in Table 1, the studies reviewed here draw on disparate sets of input criteria and constraints, and this is generally the case with similar wind farm siting studies in the literature. This makes it difficult to directly compare and contrast analysis methods, but the framework presented here has the advantage of learning from these other studies and identifying gaps and shortcomings in terms of relevant input data. Therefore, one novel contribution of this framework is the compilation of a more complete set of relevant criteria as input values. Great analytic approaches may fall short of their full potential if the datasets are missing vital criteria, and the results may suffer, even for preliminary analysis.

One thing that is clear from reviewing the literature on the subject is that in order to answer the question "Where is it feasible to locate a wind farm?" it is often beneficial to first answer the question "Where is it *not* feasible to locate a wind farm?" All four of the studies reviewed here began their analysis with this step, and this thesis has adopted that approach as well.

3.4.1 Stage 1 Evaluation: Exclusion of Non-feasible Areas

Stage 1 of this framework is to exclude unsuitable sites based on rudimentary physical, administrative, and geographical constraints. Areas including and within specified distances of National Parks, National Forests, National Monuments, state and local parks, wetlands, water bodies, military installations, populated places, airports, and areas considered critical habitat for wildlife or vegetation were excluded outright, as were areas with karst (i.e. caves, sinkholes, aquifer feeds, etc.) geology (Table 2). Areas that did not meet the constraints were excluded through a Boolean 'AND' (Yes = 1/No = 0) classification process. All layers were converted to a common cell size of 400 m by 400 m for the analysis because 500 m was the smallest buffer size, and 400 m is a scalable increment of most other distance thresholds.

Table 2: Stage 1 Evaluation criteria and constraints.

Factors	Criteria	Constraint for exclusion
Economic, Safety	Populated Place	Within 800 m (≈ 1/2 mile)
Environmental	Wetland	Within 800 m (≈ 1/2 mile)
Environmental	Water Body	Within 800 m (≈ 1/2 mile)
Environmental	Critical Habitat (IBA[1], USFW, GAP[2])	Within 1,600 m (≈ 1 mile)
Physical, Engineering	Karst Geology	Less than 100 m depth (≈ 328 ft)
Administrative, Public Use	National Park, Forest, or Monument	Within 1,600 m (≈ 1 mile)
Administrative, Public Use	State or Local Park	Within 800 m (≈ 1/2 mile)
Infrastructure, Safety	Airport	Within 1,600 m (≈ 1 mile)
Infrastructure, Safety	Military Installations	Within 1,600 m (≈ 1 mile)

[1]*Important Bird Areas as designated by the Bureau of Land Management (BLM)*

[2]*See Appendix for list of GAP Status Codes*

3.4.2 Stage 2 Evaluation: Geographical Suitability Assessment

Stage 2 identifies those areas deemed "suitable" for large-scale wind energy development through the assignment of suitability scores. These scores are calculated based on assigned grading values ($\boldsymbol{GV}$) given to the range of suitable criteria values. Grading values were derived by dividing the maximum score value (GV_{max} = 1.0) by the number of relevant criteria (n) and then subtracting this value from each successive grading value, starting from the highest ranking range of criteria values (GV = 1.0) to the constraint threshold (GV = 0.0). Criteria value ranges that were deemed unsuitable (GV = 0.0) were sometimes a function of distance where d = 0.0, but at other times represented a predetermined unsuitable class range, (i.e. wind power class and land cover class), or in the case of slope, unsuitable percentage ranges. Suitability indexes were derived for each of the Stage 2 criteria, shown in Tables 5 through 10 (below).

All layers were then reclassified to a common scale of 1 to 10 by intervals of 1, called scale values for the weighted overlay operation, with 10 being the highest suitability score, 1 being the lowest, and 0 being restricted (unsuitable) values. Some layers were distance ranges, some were classes, some were percentages, and most layers did not have exactly 10 value ranges or classes, so it was necessary to reclassify the input criteria value ranges in order to overlay them. The ArcGIS Weighted Overlay tool requires integers for the scale values, which were calculated by multiplying the grading values by 10 and rounding to the nearest integer. These scale values were used as the suitability scores.

Criteria that have a geographic dependence on the proximity to specific features, such as roads, power lines, and cities, will have suitability scores that diminish further from the feature until they reach a distance threshold where the score is zero (economically not favorable). However, criteria that deal with sources of public opposition, such as noise, visual impact, habitat conservation, and safety, would theoretically demonstrate a "distance decay" relationship where the resistance to development diminishes as the distance away from the feature increases (Van der Horst & Toke, 2010), and therefore suitability scores would also increase as a function of distance (***d***). Since this analysis deals primarily with physical and geographical constraints, minimum distance thresholds (buffers), rather than grading values, were used to identify unsuitable areas for Stage 1 (simple) criteria that showed a distance decay relationship, while grading values were used to identify unsuitable areas for Stage 2 (dynamic) criteria.

Roads and populated places (i.e. urban areas, cities, and towns) are unique examples because ideal locations would be located within a specified distance of the feature and would show an inverse distance decay relationship, but there are also visual, auditory, and safety concerns that require a buffer and show a distance decay relationship. In this case, two different thresholds are used; a minimum distance threshold and a maximum distance threshold (where $d = 0.0$). The Stage 2 criteria and model constraints are shown in Table 3.

Table 3: Stage 2 Evaluation criteria and constraints.

Factors	Criteria	Constraint
Physical, Wind Resource	Wind Power Class (WPC)	Must be ≥ 4
Physical, Engineering	Slope (percent rise)	Must be less than 20%
Environmental, Economic	Land Cover Class (LCC)	NLCD Classes 11, 12, 21-24, 90, 95 excluded
Infrastructure, Economic	Distance to Grid	Must be within 8 km (≈ 5 miles)
Infrastructure, Economic	Distance to Road	> 500 m (≈ 1/4 mile); < 8,000 m (≈ 5 miles)
Infrastructure, Economic	Distance to City	> 1,600 m (≈ 1 mile); < 16,000 m (≈ 10 miles)

While Stage 1 criteria primarily relied on a simple Boolean classification of buffered features (i.e. excluded or not), the Stage 2 criteria are a subset of the entire set of ONSWPS site selection criteria that have a fluctuating geographical dependence on some aspect of the input features. These criteria could have also been included in Stage 1 because they each have thresholds for exclusion, but they also have a graduated range of suitable values based on spatially dependent relationships with the features used to represent them that defines their level of suitability.

To eliminate redundant computational processes and save time, it was easier to evaluate these constraints through grading values using the Reclassify tool in ArcGIS. For distance-dependent criteria, the Euclidean Distance tool was used to calculate distance ranges prior to reclassification. A suitability index was then created for each of the Stage 2 Criteria that graded the input values or value ranges on a scale of 0.0 (not suitable) to 1.0 (optimal).

Wind Power

The wind resource is the most important geographically-dependent criterion, and this dataset is organized into classes based on mean annual wind density and mean annual wind speed at delineated heights above the Earth's surface (Table 4). Heights of 50-80 m are typical for utility-scale or large distributed systems (American Wind Energy Association [AWEA], 2008). Wind power classes (WPC) are based on the work of NREL, AWS Truepower, and the U.S. Dept. of Energy's Wind Powering America Program (U.S. Department of Energy, 2011).

Table 4: Wind power classes based on mean annual wind density and mean annual wind speed at 50 m height, based on Rayleigh speed distribution of equivalent mean wind power density. Data from NREL.

Wind Power Class	Wind Power Density (W/m2)	Wind Speed (m/s)
1	0-200	0.0 - 5.6
2	200-300	5.6 - 6.4
3	300-400	6.4 - 7.0
4	400-500	7.0 - 7.5
5	500-600	7.5 - 8.0
6	600-800	8.0 - 8.8
7	800-2000	8.8 - 11.9

There are various ways to assess the wind resource and different scales at which to aggregate the data. For regional analysis, the 200 m resolution data compiled by NREL was sufficient. A mean annual wind speed of 7 m/s is commonly considered the minimum range for utility-scale wind energy production (Rodman & Meentemeyer, 2006), which corresponds to WPC 4, although technology is constantly improving and approaching the possibility of being able to utilize WPC 3 for utility-scale systems. Table 5 illustrates the grading values used in this analysis.

Table 5: Suitability Index for the Wind Power Class (WPC) Layer

n	**WPC**	**Grading Value**	**Scale Value**
1	7	1.00	10
2	6	0.75	8
3	5	0.50	5
4	4	0.25	3
n/a	3	0.00	Restricted
n/a	2	0.00	Restricted
n/a	1	0.00	Restricted
n/a	-999 (no data)	0.00	Restricted

Electrical Grid

The proximity to the electrical grid is the most important distance-dependent criteria due to both the cost of constructing and integrating new transmission lines, substations, and other facilities (Ibrahim, Ghandour, Dimitrova, & Perron, 2011; Van Haaren & Fthenakis, 2011), and the costs associated with energy loss over long transmission distances, which can devalue wind energy production to the point where it is not competitive with other forms of energy (Bohn & Lant, 2009; Ibrahim, Ghandour, Dimitrova, & Perron, 2011; Rosenburg, 2008b). Since wind energy is an intermittent energy source, it requires special energy handling, storage, and transmission facilities to handle the energy fluctuations, including energy overloads to the systems during very high winds (Ibrahim, Ghandour, Dimitrova, & Perron, 2011). Proximity to the existing energy infrastructure is beneficial to offset these costs as much as possible (Van Haaren & Fthenakis, 2011). Table 6 illustrates the grading values used in this analysis.

Table 6: Suitability Index for the Proximity to Electrical Grid Layer

n	Distance from grid (m)	Grading Value	Scale Value
1	0-500	1.00	10
2	501-1000	0.89	9
3	1001-2000	0.78	8
4	2001-3000	0.67	7
5	3001-4000	0.56	6
6	4001-5000	0.44	4
7	5001-6000	0.33	3
8	6001-7000	0.22	2
9	7001-8000	0.11	1
10	> 8,000	0.00	Restricted

Cities, urban areas, and populated places

The criteria representing urban areas, cities, and populated places, which consisted of two different layers ("urban areas/cities" and "populated places") in Stage 1, was reduced to just one layer for Stage 2 analysis. The populated places layer, which included all cities, towns, and census designated places in the United States (down to a population of 10 in 4 housing units in Warm River, ID), was only used in Stage 1 because appropriate buffers needed to be set, but small cities and towns typically do not have the necessary infrastructure or energy demand to facilitate large-scale wind energy development.

Urbanized areas, on the other hand, represent both of these, but also require larger buffers to accommodate urban sprawl and a potentially larger constituency of opposition. These constraints are somewhat at odds; the “not-in-my-back-yard” (NIMBY) notion of public opposition (from things like visual or auditory concerns) would seem to promote a distance decay relationship (Van der Horst & Toke, 2010), while the electricity demand and infrastructure argument would seem to promote an inverse distance decay relationship. This thesis argues for a more pragmatic approach based on satisfying a thorough set of physical and geographical constraints, and so addresses the former through an adequate buffer and then proceeds to assign grading values based on the idea that the economics of the proximity to urban areas is more important than hypothetical public opposition.

Noise is a more quantifiable issue than visual disturbance and regulations do exist in several countries. Van Haaren and Fthankis (2011) cite a Canadian report that summarizes regulatory limits for noise in the range of 40-55 dB, while an Australian EPA report sets the limit at 35 dB (Environmental Protection Authority, 2003). Noise, or sound pressure, levels are a function of turbine height, wind speed, and distance. Van Haaren and Fthnakis (2011) developed an equation for calculating noise levels at increasing distances based on a common turbine height of 78 m (taken from the Vestas V80 model with a sound power level of 100 dB), and estimated that the noise level at 500 m distance from the turbine is approximately 35 dB. This is the basis for the 500 m buffer used in this framework, which should also suffice as a buffer for safety and visual disturbance.

Visual “pollution” is similarly a function of tower height and distance, but there is no agreeable threshold at which a person’s ability to see a wind turbine becomes a nuisance in terms of aesthetic preference. Evidence suggests that the proliferation of information about wind energy and a region's prior experience with wind energy development tend to increase public acceptance; more informed and experienced communities tend to view wind turbines positively (Jobert, Laborgne, & Mimler, 2007; Van Haaren & Fthenakis, 2011). However, there are some nuisance issues that can be largely mitigated through distance buffers, such as shadow flicker and reflective glare (Rosenburg, 2008b).

Safety is another fairly quantifiable issue and relates to precautions surrounding parts malfunctions, such as a broken blade, or ice throws (when thawing ice chunks are flung from a turbine blade). Since broken blades are extremely rare with modern turbines, safe distances have only been projected from small-scale simulations, and estimates regarding the maximum distance a fragment of a broken blade would travel from an 80 m tall turbine would be about 350 m (Van Haaren & Fthenakis, 2011). Ice throws are slightly more common, but have also been documented to be around 350 m, well within the 500 m minimum threshold for roads and populated places.

Roads

The proximity to transportation infrastructure is another important distance-dependent consideration due to the costs of constructing and maintaining new roads, which must be substantial enough to allow for the transport of extremely large turbine parts (for example, the blades on the Vestas model V80 are 180 ft. long). Van Haaren and Fthnakis (2011) estimate the cost of building new access roads to be $82,000 per kilometer, not counting the costs of land clearing, permitting, or maintenance. This clearly puts emphasis on locating sites as nearby as possible to existing roads. However, as in the case of populated places, there are aesthetic and safety concerns that require an adequate buffer. Table 8 discloses the grading values and buffers developed for this criterion. Tables 7 and 8 illustrate the grading values used in this analysis.

Table 7: Suitability index for the Proximity to Urban Area/City Layer

n	Distance from city (m)	Grading Value	Scale Value
1	0-1600	0.00	Restricted
2	1601-3000	1.00	10
3	3001-4000	0.93	9
4	4001-5000	0.86	9
5	5001-6000	0.79	8
6	6001-7000	0.71	7
7	7001-8000	0.64	6
8	8001-9000	0.57	6
9	9001-10000	0.50	5
10	10001-11000	0.43	4
11	11001-12000	0.36	4
12	12001-13000	0.29	3
13	13001-14000	0.21	2
14	14001-15000	0.14	1
15	15001-16000	0.07	1
16	> 16,000	0.00	Restricted

Table 8: Suitability Index for the Proximity to Roads Layer

n	Distance from road (m)	Grading Value	Scale Value
1	0-500	0.00	Restricted
2	501-1000	1.00	10
3	1001-2000	0.88	9
4	2001-3000	0.75	8
5	3001-4000	0.63	6
6	4001-5000	0.50	5
7	5001-6000	0.38	4
8	6001-7000	0.25	3
9	7001-8000	0.13	1
10	> 8,000	0.00	Restricted

Land Cover

Land cover is an unquestionably difficult criterion to assess because of the inability to accurately define and map different land cover types, and this is problem is compounded by the existence of more than one classification system. This thesis utilizes the National Land Cover Database (NLCD) dataset for the United States, which is based on the Anderson Level II Classification System (Anderson, Hardy, Roach, & Witmer, 1976), which provides a level of detail more than sufficient for regional analysis. Selecting the particular land use classes that are most suitable for wind energy development proved a more difficult task, as there is a lack of consensus in the literature.

This framework promotes the approach that previously disturbed (developed) land is preferable to undisturbed land. Among developed land classes, those that can support wind energy development without compromising their value, such as lands dedicated to low-maintenance crops or grazing, are preferable to other types of agricultural land where the placement of turbines may interfere with production. For undisturbed land, there seems to be agreement in the literature that areas predominantly covered by shorter vegetation species, such as grasses and shrubs, are preferable to taller vegetation cover, like forests (Janke, 2010; Malczewski, 2004; Rodman & Meentemeyer, 2006), presumably based on land clearing costs and the notion that the taller the vegetation type, the more it reduces the wind speed in that area. Barren land is theoretically more preferable based on this logic, but barren land is often barren due to the presence of rocky soils or exposed rock, conditions not necessarily conducive to the construction of massive towers. However, if engineering allows for it, barren land is preferable among undisturbed land classes.

Table 9 presents the grading values used in this analysis based on these assumptions, limited to the predefined classes from the NLCD.

Table 9: Suitability Index for the Land Cover Class Layer

n	NLCD Class Code	Land Cover Description	Grading Value	Scale Value
1	11	Open Water	0.0	Restricted
2	12	Perennial Ice and Snow	0.0	Restricted
3	21	Developed, Open Space	0.0	Restricted
4	22	Developed, Low Intensity	0.0	Restricted
5	23	Developed, Medium Intensity	0.0	Restricted
6	24	Developed, High Intensity	0.0	Restricted
7	31	Barren Land	0.7	7
8	41	Deciduous Forest	0.2	2
9	42	Evergreen Forest	0.2	2
10	43	Mixed Forest	0.2	2
11	52	Shrub/Scrub	0.6	6
12	71	Herbaceous	0.8	8
13	81	Hay/Pasture	1.0	10
14	82	Cultivated Crops	0.9	9
15	90	Woody Wetlands	0.0	Restricted
16	95	Emergent Herbaceous Wetlands	0.0	Restricted

Slope

Suitable slope for wind energy development is also difficult to determine based on the literature. Recommendations range from a maximum of 10% to 30%, but a reasonable compromise can be made at 20% as a maximum threshold for engineering and construction purposes. This unfortunately eliminates many areas with high WPC, which tend to be located on or around ridges and mountains, but these areas would likely unsuitable based on other constraints as well, such as distance from roads or cities. Rodman and Meentemeyer (2006) gave preference to ridge crests and areas of higher elevation, but they were dealing with a densely populated study area. Most studies consider slopes over 10% to be unsuitable based on responses from planning agencies or private developers (Baban & Parry, 2001; Van Haaren & Fthenakis, 2011). For this analysis, suitability scores decreased as slope increased until the 20% threshold (Table 10).

Table 10: Suitability Index for the Slope Layer

n	Slope (as % rise)	Grading Value	Scale Value
1	0 - 2.5	1.00	10
2	2.6 -5.0	0.88	9
3	5.1 - 7.5	0.75	8
4	7.6 - 10.0	0.63	6
5	10.1 - 12.5	0.50	5
6	12.6 - 15.0	0.38	4
7	15.1 - 17.5	0.25	3
8	17.6 - 20.0	0.13	1
9	20.1 - 35.0	0.00	Restricted
10	> 35%	0.00	Restricted

3.4.3 Stage 3 Evaluation: Suitability Assessment

Stage 3 of the analysis identifies those sites that are optimal for wind energy development based on a combination of ideal circumstances (i.e. those cells that have high suitability scores, larger than 5,000 acres, etc.). For this analysis, the economic viability of developing certain land areas is assessed through the weighted overlay function in ArcGIS, which will yield suitability scores for each cell in the grid. Suitability scores should theoretically reflect the most economically viable sites based on the notion that ideal physical conditions will yield the highest return on investment through the maximization of the wind resource, the minimization of development costs for electricity transport and infrastructure, and the minimization of factors that would instigate public opposition. Table 11 presents these criteria and their associated relative weights.

Table 11: Output criteria weights for Stage 3 Evaluation.

Criteria Code	Description	Criteria Weight	Overlay Weight
WPC	Wind Power Class	0.303	30
GRID	Proximity to Electrical Grid	0.303	30
URBCITY	Proximity to Urban Areas, Cities and Populated Places	0.169	17
ROAD	Proximity to Transportation Routes	0.096	10
LANDCOV	Land Cover Class	0.096	10
SLOPE	Slope (as percentage rise)	0.033	3
	sum	***1.000***	***100***

Tribal lands constitute a unique criterion because of legal and logistical constraints on development, and opposition from some tribes is very strong (The Confederated Umatilla Journal, 2012). Tribal land, which is federally owned, cannot be bought, sold, or leased by conventional means and any development on those lands must be arranged as a "special lease" through the federal government (Gamboa, 2011). Legislation is currently circulating that would change the way this is handled, but for the purposes of this analysis, it is generally considered economically unjustified to pursue sites on tribal lands. There are cases though where wind energy development is occurring or has occurred on tribal lands, and so it may be worth investigating a site located on tribal land if it has a high suitability score. This framework includes tribal lands as an additional Stage 3 constraint.

3.4.4 The Analytic Hierarchy Process (AHP)

The AHP is an heuristic algorithm that follows a hierarchical structure for multi-criteria decision making and it provides mathematical measures of consistency. For site suitability analysis it is critical that the assigned weights are logically consistent and mathematically defensible, so the AHP is used to derive the input criteria weights that will be applied to the weighted overlay technique. Figure 3 illustrates the process of determining input criteria weights for suitability analysis using AHP.

The AHP requires that the problem be diagrammed as a hierarchical structure, typically with the overall objective at the top, the criteria that impact it at the next level, the attributes of those criteria at the next level, and alternatives at the bottom (Boroushaki & Malczewski, 2008; Saaty, 1990). The hierarchical structure can be more complex (or less complex), but there is a logical threshold at which humans have trouble simultaneously evaluating options.

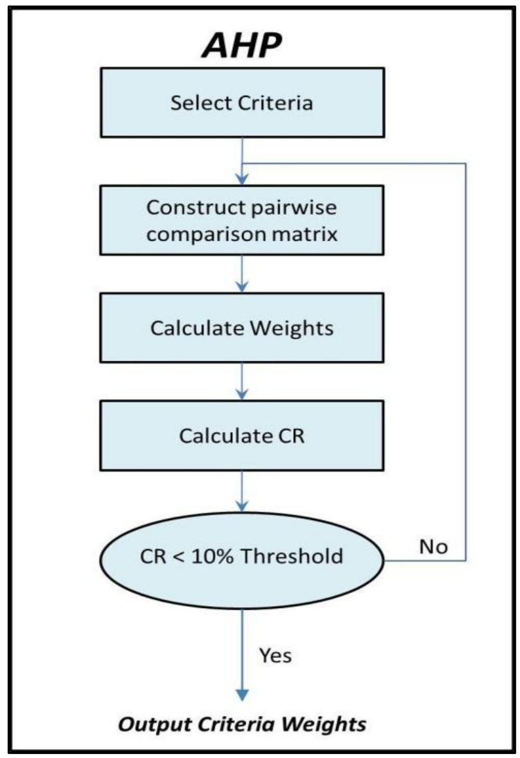

Figure 3: Schematic of the criteria weight selection process using AHP, adapted from Chen, Yu, & Khan (2010).

Based on George Miller's (1956) work with chess players, the number of criteria that humans are able to simultaneously consider is seven plus or minus two, and so generally the second layer of the hierarchy structure should not contain more than nine criteria, otherwise the structure should be reconfigured because the inherent error increases dramatically past this threshold (Saaty, 1977; 1990). For this analysis, seven criteria were selected for Stage 3 Evaluation, as shown in Figure 4. However, the last criterion, Tribal Land, was not included in the AHP matrix as a weighted variable; rather, it was evaluated separately as a final Stage 3 constraint.

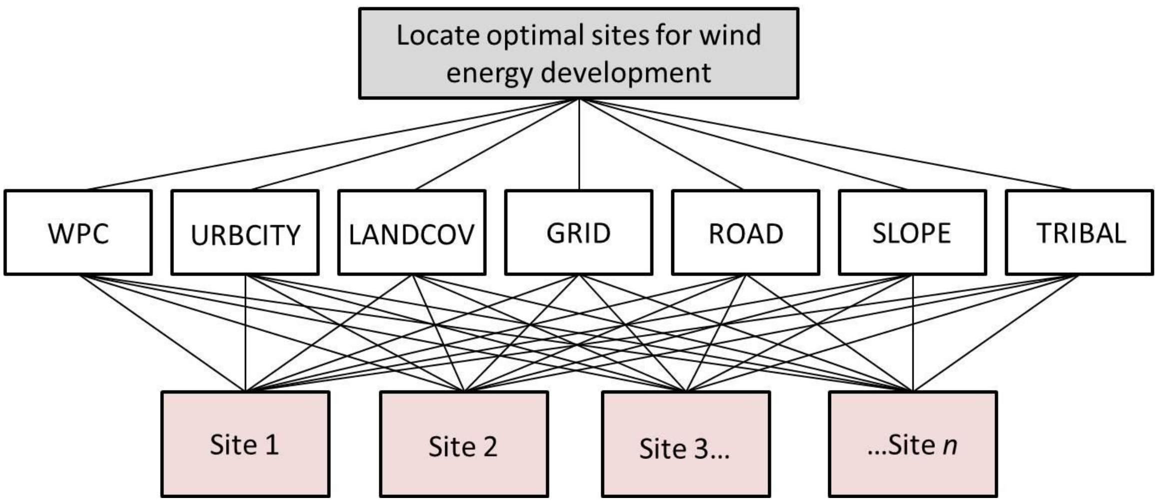

Figure 4: Schematic of the hierarchical structure of the ONSWPS Stage 3 Evaluation criteria, based on Saaty (1990).

Once the hierarchical structure has been established, the pairwise matrix can be constructed. In AHP, this process consists of ranking the relative importance of each criteria against the others in terms of its impact on achieving the overall goal (the top level of the hierarchy). The fundamental scale proposed by Saaty (1977) is used to rank the relationships amongst the criteria by importance (Table 12), and from these pairwise comparisons the pairwise matrix is created (Table 13). In MCA, it is often impossible to assign absolute values of importance to the diverse, often intangible, criteria. For example, how does one quantify the value (importance) of visual aesthetics, critical avian habitat, and proximity to the electrical grid as applied to ONSWPS site selection?

Some sort of relative scale must be used to establish a hierarchy of priority, i.e. Action A is more important than Action B. In terms of data types, it is dealing with ordinal data versus interval data; the former has the advantage of flexibility in terms of handling diverse criteria, but lacks an inherent zero and therefore cannot tell us *how much* more important one thing is over another (even in relative terms). The fundamental scale enables the conversion of ordinal data into ratio data by using an absolute scale with an inherent zero, i.e. Action A is *this much* more important than Action B. Therefore, it is possible to not only quantify the relationships amongst diverse criteria, but also to evaluate the consistency of these judgments and revise them if necessary in the pairwise matrix.

Table 12: The fundamental scale, adapted from Saaty (1990).

Intensity of importance on an absolute scale	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Moderate importance	Experience and judgment strongly favor on activity over another
5	Strong importance	Experience and judgment strongly favor on activity over another
7	Very strong importance	An activity is strongly favored and its dominance demonstrated in practice
9	Extreme importance	Evidence favoring one activity over another is of the highest possible order of affirmation
2, 4, 6, 8	Intermediate values	When compromise is needed
Reciprocals	If one activity *i* has one of the above activities assigned to it when compared with activity *j*, then *j* has the reciprocal value when compared with *i* (i.e. 5 = 1/5 or .200)	

The pairwise matrix is an *n* x *n* grid that requires input values to be assigned by the user based on research, experience, and/or expert opinion for each pairwise comparison. In AHP, these values are selected from Saaty's (1977) fundamental scale and assigned by row, meaning that the row representing each criterion is compared to each column in terms of importance. This also means that the column representing each criterion will hold the reciprocal value of the fundamental scale value assigned to the row.

At the end of each row the *n*th root value is calculated by multiplying all of the criteria values together and taking the *n*th root, in this case n = 6, so each product is raised to the 1/6 power. This produces a normalized value for each row, and the *n*th root values are summed together to provide a denominator for the priority vector calculation. The priority vectors are calculated by dividing each row's *n*th root value by the summed *n*th root value. The priority vectors are the output criteria weights for each row (each criterion), now normalized against the matrix so that the sum of the priority vectors is equal to 1.0.

Table 13: Pairwise matrix for ONSWPS site selection criteria showing fundamental scale values, reciprocal values, *n*th root values (*n*=6), priority vectors (relative weights), the principal eigenvalue (λ_{max}), the consistency index (*CI*) value, and the consistency ratio (*CR*) value, based on Saaty (1990).

n		1	2	3	4	5	6		
		WPC	**SLOPE**	**LANDUSE**	**GRID**	**ROAD**	**URBCIT**	***n*th Root**	**Priority Vector**
1	**WPC**	1	9	3	1	3	2	2.33482	0.303
2	**SLOPE**	0.111	1	0.333	0.111	0.333	0.200	0.25491	0.033
3	**LANDUSE**	0.333	3	1	0.333	1	0.500	0.74184	0.096
4	**GRID**	1	9	3	1	3	2	2.33482	0.303
5	**ROAD**	0.333	3	1	0.333	1	0.500	0.74184	0.096
6	**URBCIT**	0.500	5	2	0.500	2	1	1.30766	0.169

λ_{max} = 6.01255 *CI* = 0.00251 *CR* = 0.00202

Once the pairwise matrix was created and the formulas were input (using Microsoft Excel), it was possible to adjust the criteria input weights until the lowest set of *CI*, *CR*, and λ_{max} values were found. Noting that a matrix is consistent if and only if: $\lambda_{max} = n$ (Saaty, 1977), the goal was to adjust the input values until λ_{max} was as close to 6.00000 (n = 6) as possible, in this case 6.01255. The *CI*, which measures the deviation between λ_{max} and n in order to assess inconsistencies in the pairwise comparisons, was calculated from Equation 1. In this case, the calculation was (6.01225 – 6)/(6 – 1) = 0.00251, and from this the *CR* can be calculated using Equation 2.

As discussed in section 3. 6, a number of important calculations come from the pairwise matrix that evaluate *consistency*, which in this context refers to *consistency of judgment*, but it has a specific meaning in the mathematical structure of AHP. Consistency is measured for two primary reasons and therefore has two imperative functions:

1) To evaluate the consistency of the user-assigned input criteria values in regards to the dominance of one row (one criterion or action) over another in terms of the order of magnitude of importance; these judgments must be consistent to preserve the order or rank of the criteria in the pairwise comparisons (Saaty, 1990). For example, if Criteria A has a 2:1 importance over Criteria B, and Criteria B has a 2:1 importance over Criteria C, and Criteria C has a 2:1 importance over Criteria A (A > B > C > A), then these judgments are logically inconsistent (or invalid) and also mathematically inconsistent. A row can demonstrate dominance over another either directly (i.e. A > B) or indirectly (i.e. A > B because A > C and C > B) and these ranks must be preserved throughout the matrix. This order of dominance can be demonstrated in as many steps as the number of criteria (n), and this is why the nth root is calculated for each row.

2) To control error in judgment by promoting the homogeneity of input values, i.e. keeping the judgments within an order of magnitude between criteria; this is why the fundamental scale is only 1-9. A larger difference in input values has potentially larger error, while smaller differences in input values are less affected by perturbations. The number of criteria (*n*, or λ_{max} in a consistent matrix) also play an important role in measuring the inherent error in judgment because the larger *n* gets, especially beyond the 7±2 threshold, the larger the potential error becomes, and the smaller *n* is the more stable it is to random perturbations. The difference between λ_{max} and *n* is therefore an important measure of consistency (Saaty, 1977; Saaty, 1990; Saaty & Vargas, 2001).

While there are several measures of consistency in the AHP, the CR is the most indicative of whether the judgments are acceptably consistent, and it is imperative that these values are significantly different than those that would be derived from random input values. The Random Index (*RI*) values used in this analysis come from a lookup table (shown in Table 14) based on the work of Saaty and Vargas (2001), who ran thousands of iterations to derive the index.

Table 14: Random Index (*RI*) values, adapted from Saaty & Vargas (2001).

n	*RI* value
1	0.00
2	0.00
3	0.58
4	0.90
5	1.12
6	1.24
7	1.32
8	1.41
9	1.45

The *RI* values are directly related to the number of criteria (n) in the analysis, and for this application with seven criteria the corresponding *RI* value is 1.24. This value becomes the denominator in Equation 2, and a matrix is generally considered consistent if $CR < 10\%$ (Boroushaki & Malczewski, 2008; Chen, Yu, & Khan, 2010; Saaty, 1990; Tegou, Polatidis, & Haralambopoulos, 2010). For this analysis the *CR* value was calculated (0.00251/1.24) = 0.00190, or approximately 0.19%, which is well below the 10% threshold.

3.5 SA Methodology

Several SA approaches are found throughout the literature, and the most common have to do with changing the input values, changing the relative importance of the criteria (i.e. Saaty's fundamental scale values), or changing the criteria weights. There are also different weighting schemes that can be used within each of these approaches, either by substituting random values or by changing the values by a defined interval or percentage, or by giving all criteria the same weight or zero weight when compared to all others.

This thesis is interested primarily in documenting the effects of perturbations in the input criteria weights. A combination of approaches was used in this analysis, both drawing from the studies reviewed earlier and incorporating another approach from the literature. Baban and Parry (2001), Rodman and Meentemeyer (2006), and Tegou et al. (2010) all applied the equal weighting scheme as part of their SA, and it is a logical baseline for comparative purposes. This thesis applies the equal weighting scheme to the criteria weights as the first phase of the SA.

This thesis also applies an SA method known as One-At-a-Time, or OAT, that allows the user to alter single input values by a certain percentage interval and then measure the impact of that change relative to the other criteria, which must be adjusted accordingly so that the criteria weights still sum to 1.0. The isolation of variables eliminates ambiguity and improves the comparability of the results (Chen, Yu, & Khan, 2010). A percentage interval of ± 20% was chosen as the percent change (pc) used in this analysis, which was applied to each of the six Stage 3 criteria individually and the changes were measured in acres of suitable land (Table 15, next chapter). The formula used to calculate the weight (W) of the main criterion under consideration (c_m) is :

$$W(c_m, pc) = W(c_m, 0) + (W(c_m, 0) \times (pc)) \tag{3}$$

where $W(c_m,0)$ is the original input weight of (c_m) and $W(c_m, pc)$ is the weight of that criterion at a given pc (in this case, ± 20%). The formula for calculating the adjusted weights of the other criteria is:

$$W(c_i, pc) = \left(1 - W(c_m, pc)\right) \times \frac{W(c_i,0)}{1-W(c_m,0)} \tag{4}$$

where (c_i) is the ith criterion and $W(c_i, 0)$ is the original (AHP-derived) input weight of the ith criterion (Chen, Yu, & Khan, 2010). With OAT, the user can choose to run the SA at any number of percentage increments. This thesis chose to examine the data at 5% increments to the ± 20% threshold, plus the base run (the original AHP-derived criteria weights), yielding nine total runs.

3.6 Technology

This analysis was conducted using ArcGIS 10.0 Desktop software including Spatial Analyst and 3D Analyst extensions. Models were constructed using ArcGIS ModelBuilder through the ArcMap/ArcINFO interface. Maps were created using ArcMap and exported in JPEG format at 200 dpi. The Microsoft Office 2010 Suite (Word, Powerpoint, and Excel) was employed to create the main document and all associated graphs, tables, and figures. The hardware used was the Windows 7 (Service Pack 1) operating system running on a 64-bit HP 2000 Notebook PC laptop with an AMD E-350 processor, 3 GB RAM.

3.7 Data Processing

The first step was to collect the necessary datasets and convert them into usable forms using ArcGIS 10.0 geoprocessing tools. For this type of analysis, working with a grid system was the most effective means of calculating values for particular locations. This way each grid unit (or cell) in the study area would have an integer value and these values could be altered based on the weights assigned to them, yielding a *suitability score* for each cell. However, most datasets are available as vector-type data and so several of the datasets had to be converted to grid-based (raster) data prior to analysis.

A final grid resolution of 798 m (NAD_1983_Oregon_Statewide_Lambert projection) was chosen for this analysis because it was the largest cell size amongst the datasets, found in the Digital Elevation Model (DEM). All other datasets were converted to this cell size because the accuracy of the spatial data can be no greater than the coarsest resolution found in the datasets. Although a finer resolution could be obtained by resampling the DEM, the chosen cell size was suitable for regional analysis, and this coarser cell size reduced computer processing time. To further reduce the computation time of processing and analysis, all layers were first clipped to a common regional extent, slightly larger than the study area (for most layers, the boundaries of Washington, Oregon, and Idaho were used for cartographic purposes).

The Land Cover layer required extensive manual processing because it was only available in smaller extents than the study area due to the large size of the files. Two raster files were required to cover the study area, each over 10 GB as individual layer packages, and they were added to the geodatabase through the *Create New Raster* tool. The two rasters were loaded into the new raster file using ArcCatalog and then clipped to the regional extent of the other layers. The original rasters were converted from WGS84 to NAD83 by adding them into the geodatabase through the *Load Data* function. The resolution, which was nearly two orders of magnitude smaller than the cell size used in this analysis, was adjusted by using the *Export Data* function and manually specifying the new cell size. This new raster was then added to the geodatabase and then re-symbolized in ArcMap based on the National Land Cover Dataset (NLCD) classification scheme.

Once all the datasets had been converted to a common format (i.e. same coordinate system, same cell size, proper extent, etc.), they were added to a geodatabase in ArcGIS. The geodatabase includes feature datasets for Administrative, Infrastructure, and Environmental themes, and includes the raster datasets. Feature topology was not enforced because it was not critical for this analysis at this scale.

The analysis was carried out in three stages using ArcGIS 10.0 ModelBuilder. For Stage 1, the Euclidean distance was calculated from each feature to a maximum distance of 2,000 m (slightly further than the largest buffer), producing new rasters as outputs. The new rasters were manually converted to a binary scale (Yes = 1/No = 0) using the *Reclassify* tool. Areas within the buffer thresholds were assigned values of zero, while the remaining areas were given a value of one. These outputs were then combined into a single layer through the *Mosaic-to-New Raster* tool with a minimum mosaic operator, and then the relevant areas (buffered features) were selected using the *Con* tool, which uses conditional statements to select only the desired cells (those with values of zero). Areas with values of '1' were discarded in Stage 1 for illustrative purposes, but were reused in Stage 3 as a mask raster.

A *Euclidean Distance/Reclassify* tool combination was used instead of a *Buffer/Polygon-to-Raster* tool combination strictly to save processing time. The *Buffer* tool only works with feature classes (vector layers), and the large size of the datasets used in this analysis often required several hours to calculate the polygon geometry, and then the new polygon layers would need to be converted back to rasters for the overlay operation, a process that also took hours for each operation. The *Euclidean Distance* tool accepts either feature classes or rasters as inputs and produces a raster as an output, thus effectively doing the same thing as buffering in a fraction of the time. The *Reclassify* tool could be used to set the buffer thresholds, and the *Con* tool could be used to select the cells that correspond to the buffered areas. A diagram of the Stage 1 Model is shown in the Appendix.

Stage 2 required less significantly less processing time than Stage 1, in part because there were less input data layers, but also because all of the Stage 1 layers were in vector format and many of these layers consisted of extremely large numbers of features, which not only take longer for ArcMap to process but also to render. Stage 2, with only three vector layers and three raster layers, was much more efficient. A similar approach to Stage 1 was used with the *Euclidean Distance* tool being used for the distance-dependent criteria (again using the 2,000 m threshold), and then all layers were reclassified to a scale compatible with the *Weighted Overlay* tool in ArcGIS (i.e. 1 through 10 by intervals of 1) and then given a scale value (see Section 3.4.2) in the *Weighted Overlay Table*. The AHP-derived criteria weights were then entered into the *Weighted Overlay Table* prior to running the tool. The output raster from Stage 2 was a suitable areas layer based on the AHP-derived criteria weights.

The Stage 3 Model began with creating a mask layer that represented all non-excluded areas from Stage 1. The mask layer could be used to extract (select) the suitable cells from the Stage 2 Model outputs, as well as the alternatively weighted layers produced in the SA, that were not located in a buffered zone from the Stage 1 Model. This approach was effective because the suitable cells retained their original suitability scores and one layer could be used repeatedly on as many layers as necessary, yielding consistent geographic boundaries for site selection.

The second phase of the Stage 3 Model consisted of identifying optimal sites by using the mask raster to eliminate all cells that corresponded with Stage 1 excluded areas from the Stage 2 AHP-derived suitable areas layer. The output raster from this operation was then converted to polygons so that the geographic area could be calculated, and then polygons larger than 5,000 acres were selected as optimal sites. This part of the model was rerun with the input rasters from the SA for comparative purposes.

The 5,000 acre threshold was chosen to accommodate utility-scale wind farms, which vary tremendously in size, but it cannot be overlooked that large wind farms require large continuous tracts of land. Although the space between the turbine towers can be used for other activities (Rodman & Meentemeyer, 2006; Rosenburg, 2008b) and the 'footprint' of the towers is relatively small (2-5%) compared to the total wind farm area (Kuvlevsky Jr., et al., 2007), the turbines must be located as close together as possible to achieve maximum energy transmission and storage efficiency without compromising the ability of the turbine blades to "capture" the wind directly. The turbine array (positioning) is therefore extremely important in order to avoid potential losses due to interference from the wake created by other turbines, and sufficient space is required (Dabiri, 2011).

Estimates are variously described throughout the literature as requiring 5-15 turbine diameters of spacing between towers, and estimates for the overall size of wind farms range from 0.25 acres/tower (National Renewable Energy Laboratory [NREL], 2012) to 2-3 W/square meter (Dabiri, 2011) to 40-200 acres/MW (Denholm, Hand, Jackson, & Ong, 2009). For this analysis, a theoretical 50 MW wind farm is used as the baseline, utilizing a safe average of 100 acres per MW.

At this stage of the analysis, some tradeoffs become apparent due to the requirement for large tracts of land. If one wishes to examine only the areas with the highest suitability scores (i.e. 9 or 10), they will most likely eliminate any large polygons from the analysis since there were relatively few cells with those scores (Figure 5) and those cells were relatively well distributed (Figure 6). However, if one is willing to examine the entire range of remaining cells, then not only are there more large polygons to choose from, but adjacent polygons can be combined to identify larger suitable sites.

Since the requirement for large tracts of land is also a suitability constraint and any cells remaining at this point in the analysis have already satisfied several critical constraints (only cells with suitability scores ≥ 5 remain after Stage 3), this framework treats all remaining cells as a single category: *suitable*. Also, as will be discussed further in Chapter Four, the geographic location of the suitable cells is nearly identical under all weighting schemes, but the values of the individual cells changes within those locations, suggesting that the value of an individual cell is not as important as the fact that a suitable cell exists at that particular geographic location.

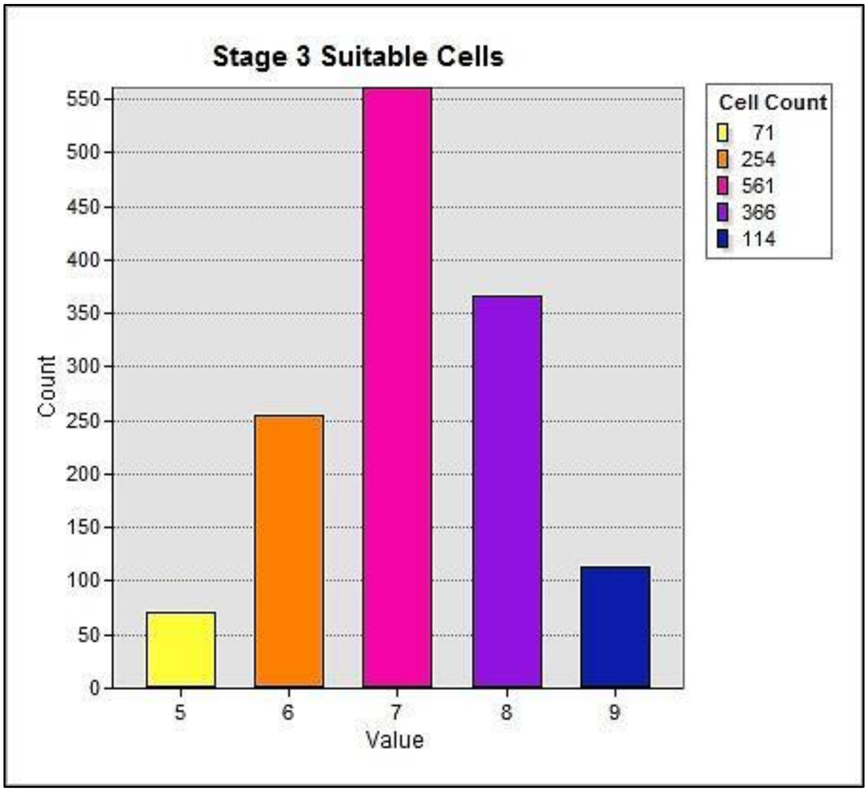

Figure 5: Histogram showing the number of cells by suitability score remaining after "extraction by mask" in Stage 3, based on the AHP-derived criteria weights.

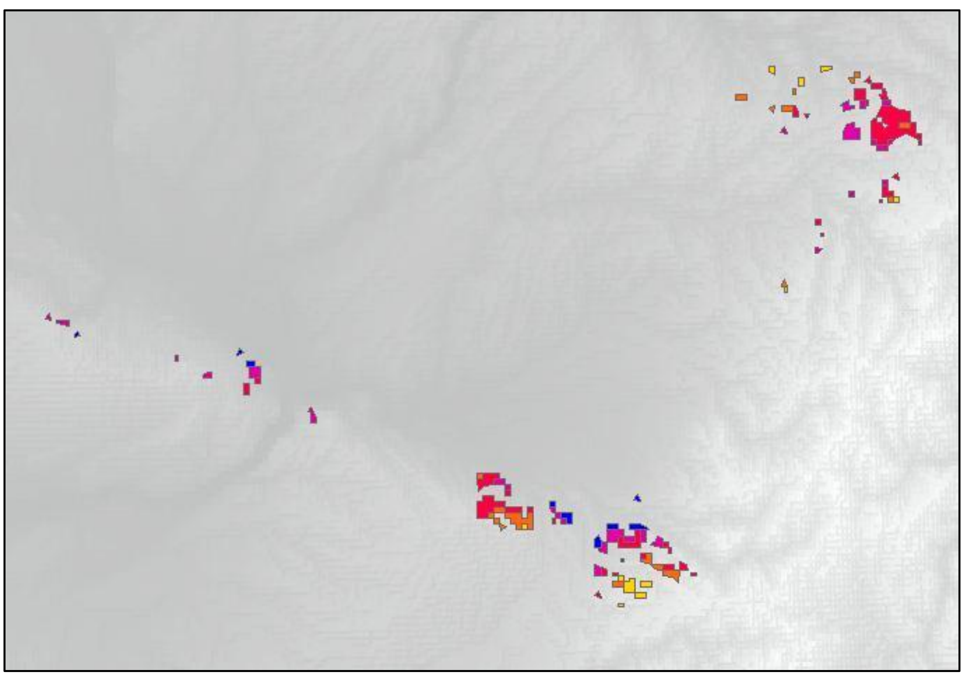

Figure 6: Sample spatial distribution of the suitable cells layer depicted in Figure 13.

For the final phase of the Stage 3 Model, neighboring polygons (within a distance of 1600 m) were joined using the *Aggregate Polygons* tool, and polygons larger than 5,000 acres were selected from that layer. All polygons smaller than 5,000 acres were discarded for this analysis, despite their suitability scores, and the study area was examined for the locations of the remaining polygons to select a detailed regional extent to analyze for the SA.

In summary, Stage 3 identifies optimal sites as those that:

- Are not located in the excluded areas identified in Stage 1.
- Have suitability scores greater than ‘0’ based on the Stage 2 constraints.
- Are located on sites greater than 5,000 acres.

CHAPTER FOUR: RESULTS AND DISCUSSION

One of the primary outcomes of this thesis is the creation of a series of maps to provide quick access to site suitability information. Static maps were created for each evaluation stage that contain different types of information. For Stage 1, the maps show the areas excluded from the analysis, for Stage 2 the maps show the areas considered suitable for wind energy development based on graded suitability scores (high=10; low=0), and the Stage 3 maps show the optimal areas for development based on an overlay of the Stage 1 and Stage 2 constraint maps and a minimum size constraint (5,000 acres). Additionally, a series of maps and figures were included to help visualize the results of the sensitivity analysis (SA). The locations of existing wind farms was shown in several of the maps as a means of assessing the models in "real-world" terms.

4.1 Stage 1 Evaluation Results

The objective of Stage 1 was to remove unsuitable areas from the analysis based on simple criteria and their associated buffers. Figure 7 shows the results of the Stage 1 Model, and it is evident from the map that the majority of the study area is considered unsuitable for wind energy development at this stage. It is also intriguing that most areas with high WPC are located within the excluded areas, as are many of the existing wind farms. This is largely due to the presence of the Cascade Mountain Range (running North/South on the left-hand side of the map) which has very high WPC, but has unsuitably steep slopes and is primarily U.S. National Forest land or National Parks.

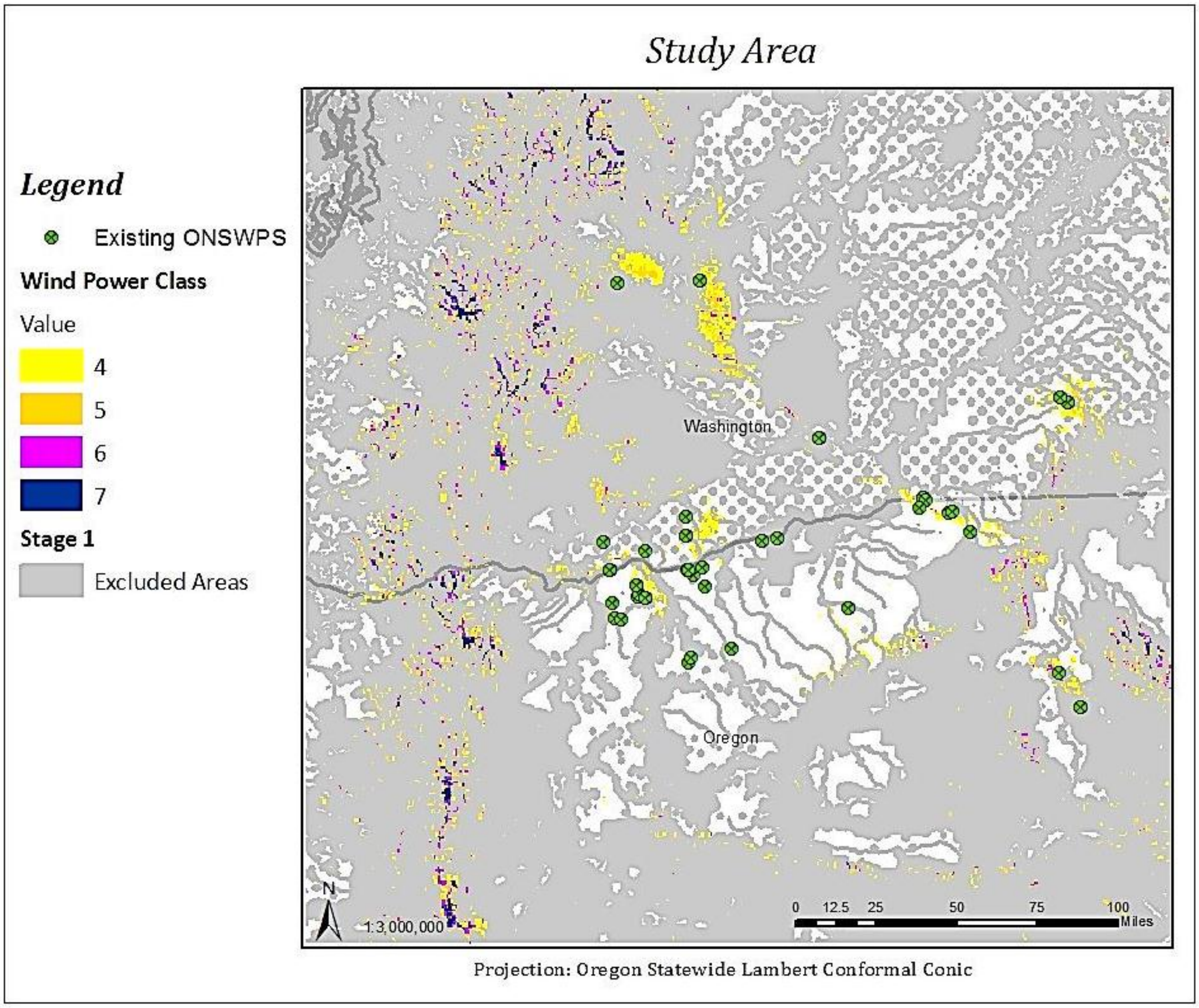

Figure 7: Stage 1 constraint map showing areas excluded from the analysis (unsuitable cells), the locations of existing wind farms, and areas of high WPC.

Significant portions of Washington and Oregon are designated as National Forests, therefore excluding vast tracts of land that have suitable-to-high WPC values, and most of the land that has the highest WPC. Unfortunately for the wind energy industry, National Forests are federally-owned land that is principally off-limits to development, but there is evidence to suggest that they harbor abundant wind resources. Figure 8 shows how much excluded land from Stage 1 is due solely to the existence of National Forests. This is currently a controversial topic throughout the country (Adkins, 2009; Streater, 2012) and we can expect to hear more about it in the next few years as states try to reach ambitious Renewable Portfolio Standards (Bohn & Lant, 2009; Rosenburg, 2008a; Van Haaren & Fthenakis, 2011).

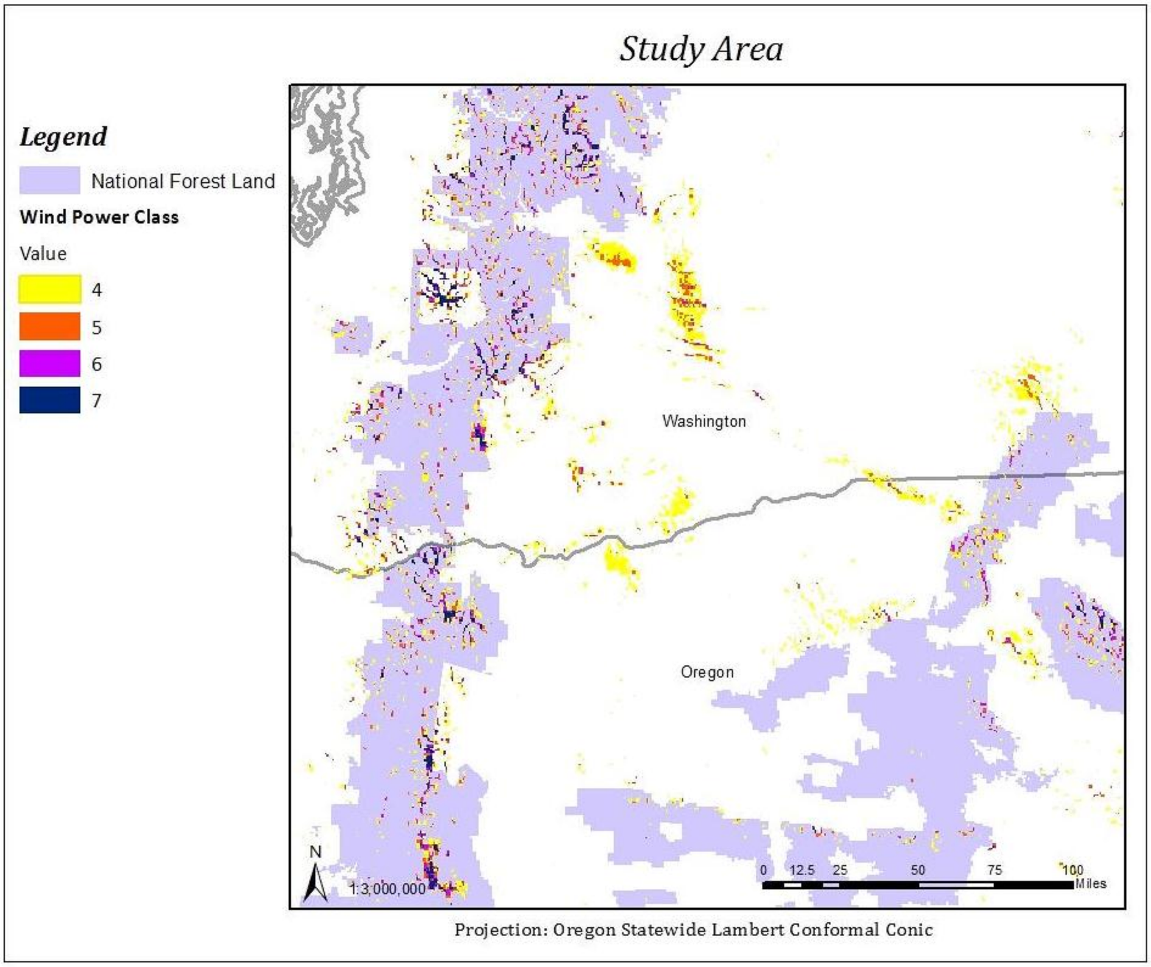

Figure 8: Map showing areas with high WPC and U.S. National Forest Land.

In the literature it is often cited that forested land is less desirable than open land because stands of trees tend to reduce wind speeds and therefore reduce wind power potential (Baban & Parry, 2001; Hansen, 2005; Janke, 2010; Ramirez-Rosado, et al., 2008; Rodman & Meentemeyer, 2006; Tegou, Polatidis, & Haralambopoulos, 2010; Van Haaren & Fthenakis, 2011). However, looking at Figure 9 (below), it is clear that this assumption may not always be true for large-scale wind power, which is typically measured at a height of 50-80 meters, well above most forest stands.

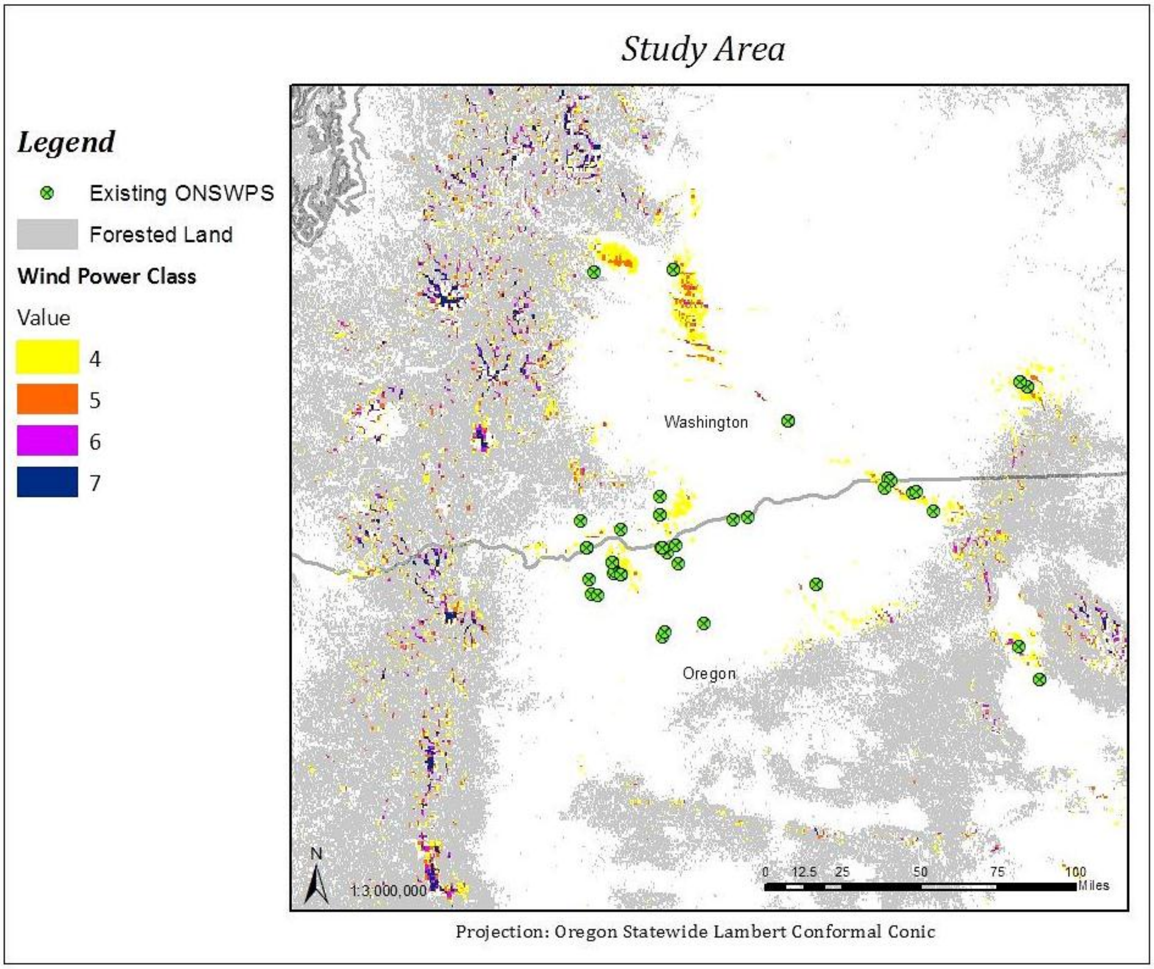

Figure 9: Map showing forested land cover, locations of existing wind farms, and areas with high WPC.

In fact, most of the areas with the highest WPC in the study area are located within land cover classes defined as evergreen, deciduous, or mixed forest. The argument then becomes one of the cost of clearing forested land compared to other types of land cover. Van Haaren and Fthenakis (2011) estimate that the cost for clearing forested land for a 50

MW wind farm to be approximately $3,000 per acre, compared to $40-60 per acre for grassland, shrubs, barren land, and cropland. For that reason, forested land was removed as a Stage 1 constraint and was assigned a suitability score of 2 in the Stage 2 analysis, therefore representing an economic constraint rather than a physical constraint.

4.2 Stage 2 Evaluation Results

In Stage 2, the goal was to locate suitable areas for wind energy development based on a set of six dynamic criteria constraints. Suitability indexes provided the basis for this assessment, and the criteria weights were derived through AHP. The ArcGIS weighted overlay tool was used to identify the feasible sites within the study area, and suitability maps were produced from the Stage 2 Model (Figures 10 and 11) showing the graded values of the suitable areas.

It is striking how much area is considered unsuitable based on the results of the Stage 2 Model. Perhaps more intriguing is comparing the preliminary results of the two different approaches (Table 15). Stage 1, a subtractive approach based on nine input criteria, reduced the amount of area under consideration (the study area) from approximately 45.8 million acres to 9.6 million acres of suitable land area, a difference of approximately 79%. By evaluating only the areas that met critical suitability requirements, the Stage 2 Model reduced the amount of suitable area by over 99% using just six input criteria and their associated suitability scores.

Table 15: Acreage statistics based on Stages 1 and 2 of the analysis.

	Acres	Percent Reduction	Percent of Study Area
Study area	45,806,472	0	100
Stage 1 Excluded Area	36,206,408	21.0	79.0
Stage 1 Remaining Area	9,600,064	79.0	21.0
Stage 2 Suitable Area > 0	185,009	99.6	0.4
Stage 2 Suitable Area > 7	127,360	99.7	0.3

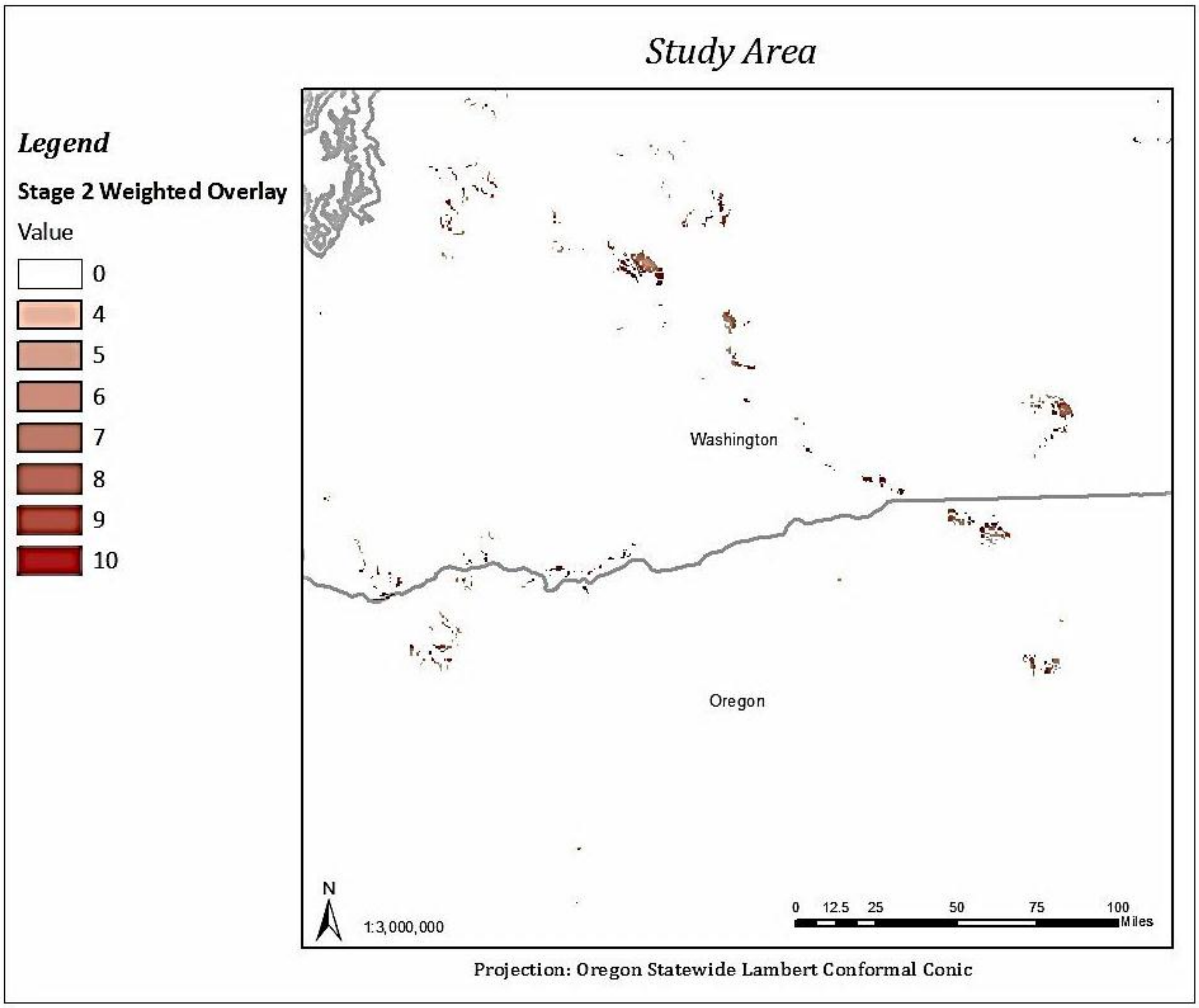

Figure 10: Stage 2 suitability map showing the results of the weighted overlay operation using the AHP-derived criteria weights (10 = most suitable; 0 = unsuitable).

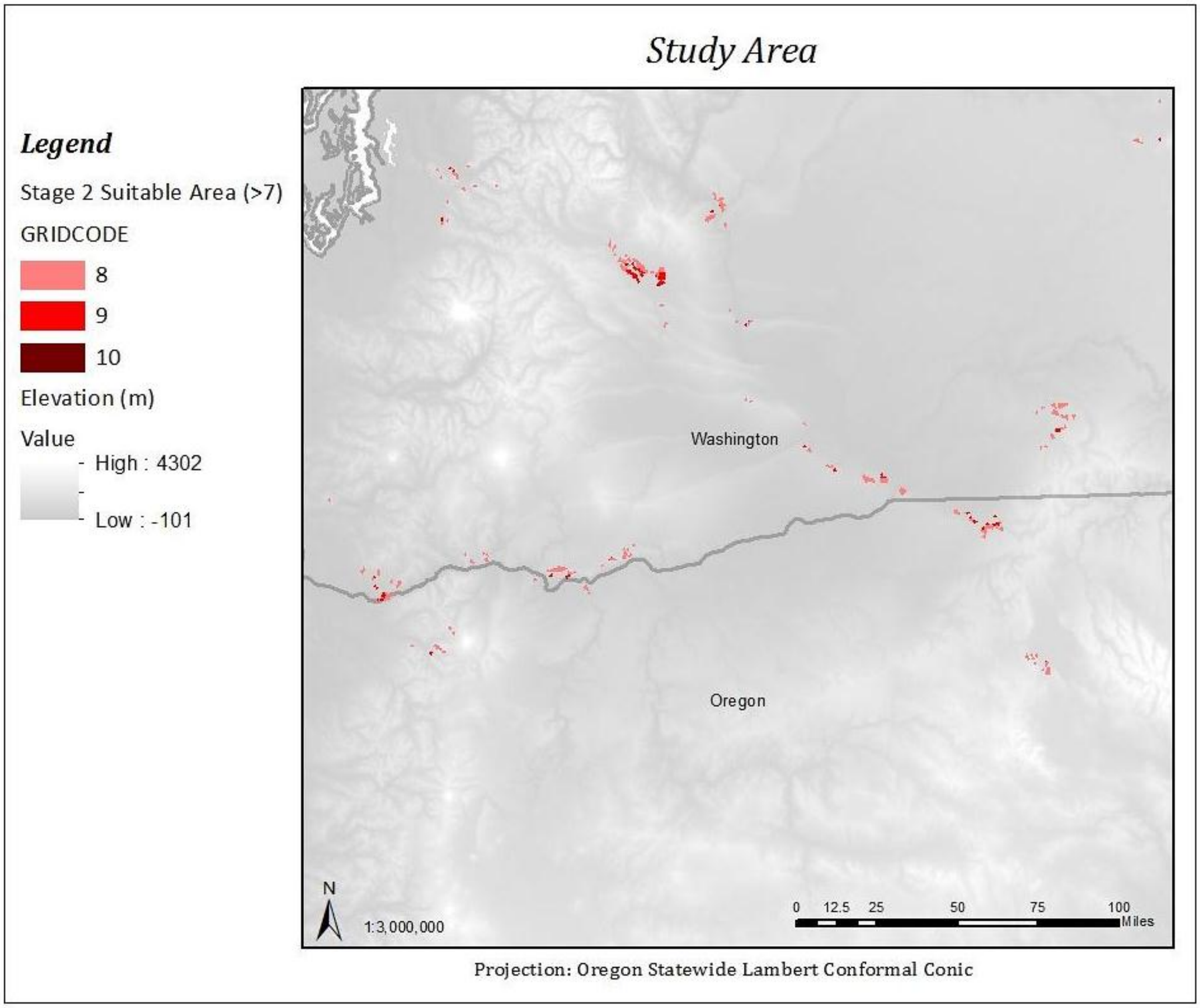

Figure 11: Stage 2 suitability map showing only areas with the highest suitability scores.

The differences are visually subtle at this scale, but there is a difference of 57,650 acres between the number of acres that are considered highly suitable (suitability score ≥ 8) and all suitable areas (suitability score > 0). In a table this difference may look significant (and it is considering how many wind turbines could fit on 57,650 acres), but the advantage of GIS visualization is that we can see where those additional acres are located on a map and draw different conclusions.

One conclusion from comparing the two maps is that the geographic distribution of the suitable cells and the highly suitable cells is nearly identical, meaning that one won't find highly suitable cells in areas where no other suitable cells exist. This makes sense because most of the graded values were distance-dependent, but it also supports the notion of spatial autocorrelation, which is a measure of the probability that features in space are randomly distributed.

The first law of geography, often called Tobler's Law, states that "Everything is related to everything else, but near things are more related than distant things" (O'Sullivan & Unwin, 2010). In this case, we would expect suitable cells to be located near one another, and highly suitable cells to be located near other suitable cells, because they share similar geographic qualities. In spatial statistics, Moran's *I* is often used to measure spatial autocorrelation. An example of the results of Moran's *I* are shown in Figure 12 for the layer representing suitable areas (suitability score > 0). The results of the Moran's *I* test are shown here in a graphic report, automatically generated by ArcGIS (Figure 12).

The results confirm that these areas are not randomly distributed, which is as expected, and they indicate that the suitable areas are indeed very strongly clustered. We see a similar result when examining the areas with suitability scores ≥ 8, although not nearly as strongly clustered (Table 16). This can likely be explained by the smaller number (n) of features (polygons) under consideration, and by the fact that the 235 features that made up the difference between the two layers were highly clustered neighboring features with distance-dependent values, thus leaving larger distances between polygons with higher values. In both cases, the results of the Moran's *I* test show a statistically significant clustering of features.

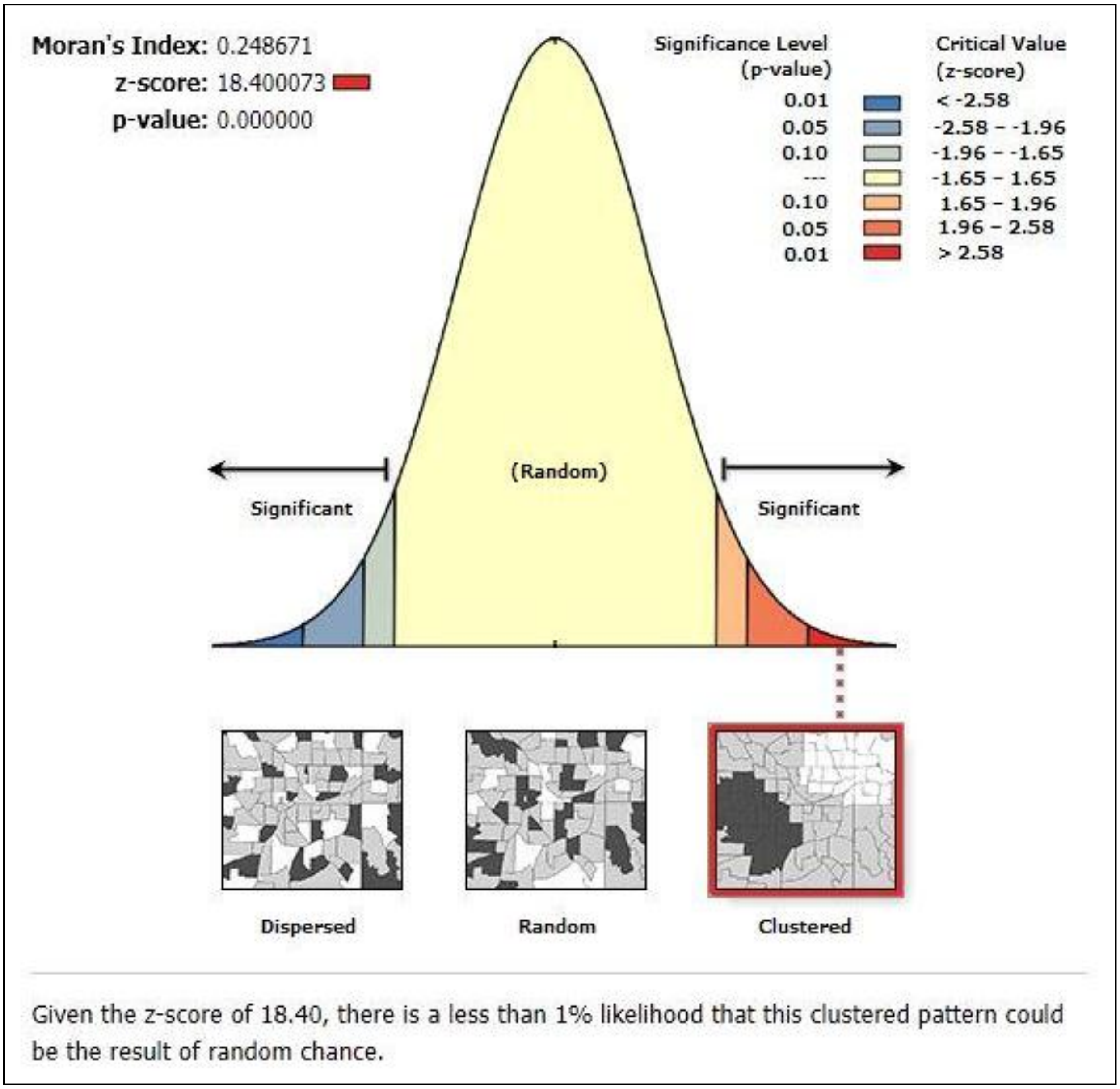

Figure 12: Results of Moran's *I* for the Stage 2 suitable areas (> 0) layer.

Table 16: Results of Moran's *I* for both Stage 2 evaluation layers.

Layer	Moran's Index	Z-score*	p-value	*n*
Stage 2 Suitable Area ≥ 3	0.248671	18.400073	0.000000	540
Stage 2 Suitable Area ≥ 7	0.095718	4.502179	0.000007	305

**For Moran's I, the Z-score is a measure of the variance between each pair of target feature values and the mean of all feature values.*

Since there is confirmation of a geographical pattern (a strong clustering of features), it may also be useful to investigate whether there is clustering of particular values. Moran's *I* only measures the distribution of *similar* feature values, but it does not measure whether there is clustering of high or low values across the entire study area. Clustering of high values, called "hot spots" in spatial analysis (and conversely "cold spots" for clusters of low values), can provide some additional insight into the suitability of a particular region (based on the selected input criteria) and perhaps explain why many existing wind farms are located in areas not considered highly suitable by technical standards.

For this type of analysis, the Getis-Ord G-statistic is often used, which measures the distribution of high or low values in a given area based on distance thresholds set by the user, and this is compared with an expected G-statistic calculated by the GIS (a random distribution). The Z-score is then calculated to test the significance of the result (i.e. whether or not it is significantly different from random). Again, we can expect that there is clustering of high values because the input feature class is based on the modeling of the input criteria in Stage 2, which selected only those cells with high suitability values. In this case, one might expect the hot spot map to look very similar to the one in Figure 11 in terms of the spatial distribution of cell values.

However, the results of the hot spot analysis indicate that there are clusters of high values that differ from the general geographical distribution of highly suitable cells from the Stage 2 weighted overlay. The maps in Figure 13 display the results for a sub-region of the study area where large clusters of suitable cells were found in the Stage 2 analysis, and there is a significant visual difference in the clustering of high values between the two maps. For example, the cell clusters to the east and southeast in the upper map appear to have about the same amount of highly suitable cells as do some of the other clusters in the northwest and middle parts of the map, yet they received significantly lower Z-scores in the Getis-Ord G-statistic hot spot analysis.

The hot spots indicate areas that are especially good candidates for wind farm sites, represented in the lower map in Figure 13 by dark red areas. In the maps presented here, the darker the red, the more significant the clustering of high values, while the light yellow areas represent no significant clustering of high or low values, and the darker the blue, the more significant the clustering of low values. However, the cells identified as hot spots are still subject to further geographical analysis during the Stage 3 Evaluation, as many of the cells may be located within areas identified as unsuitable for development during the Stage 1 analysis, and/or they may not be in areas that meet the final Stage 3 constraint requiring continuous land areas greater than 5,000 acres.

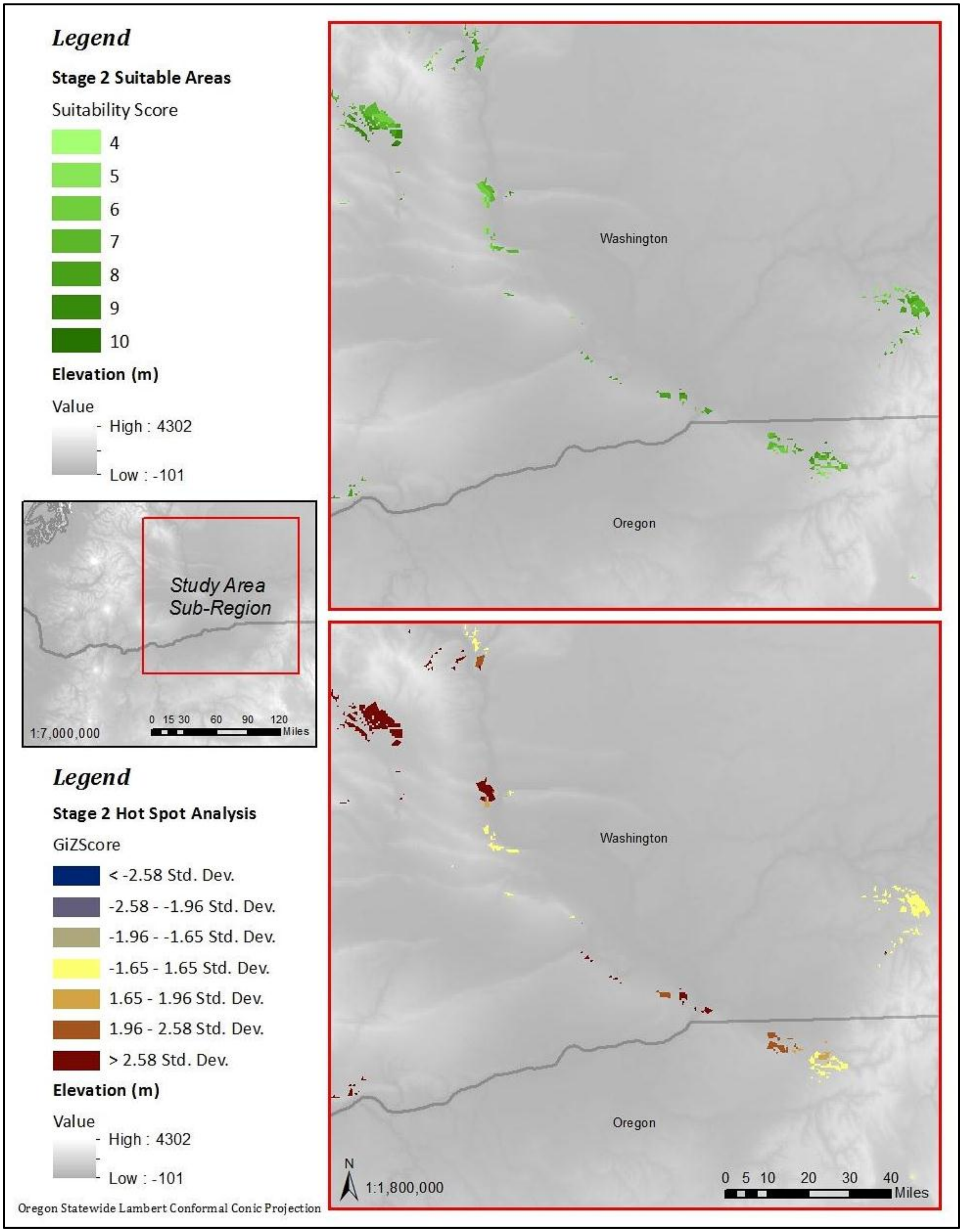

Figure 13: Map details showing the results of the Getis-Ord G-statistic test for Stage 2. In the lower map, "hot spots" (clusters of high values) are shown in dark red.

4.3 Stage 3 Evaluation Results

The Stage 3 Evaluation consisted of overlaying the Stage 1 constraint map with the Stage 2 suitability map to yield an optimal areas map. The results of this overlay operation (Figure 15) show that a large percentage of suitable cells from the Stage 2 AHP-derived weighted overlay are located in areas identified as non-suitable in Stage 1, demonstrating why it is valuable to approach the problem from different perspectives. Relying only on one approach or the other limits the effectiveness of the models and reduces the amount of information contained in the maps. For example, if User A and User B were both tasked with finding good sites for a wind farm and each used a different approach, then they might very well come to completely different conclusions. This framework works conceptually like a Venn Diagram (Figure 14), which makes sense because it is built on Boolean logic.

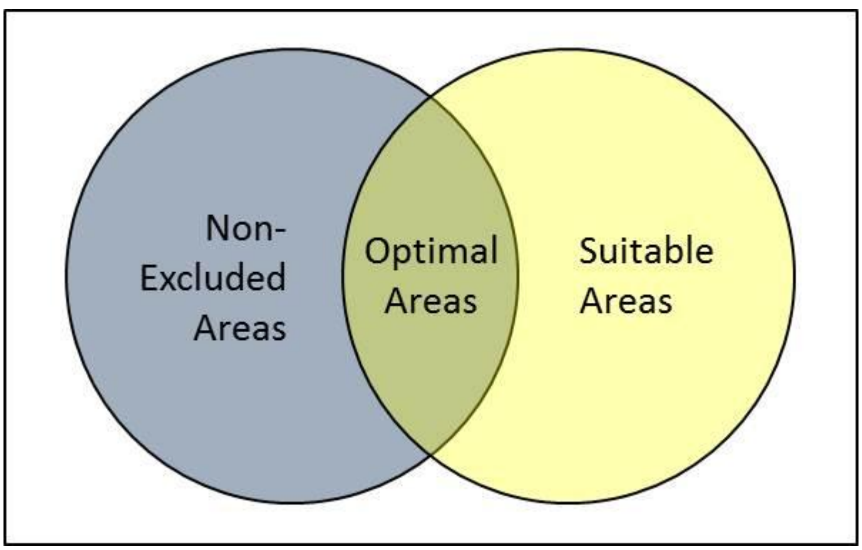

Figure 14: Venn Diagram representing the three stages of ONSWPS evaluation.

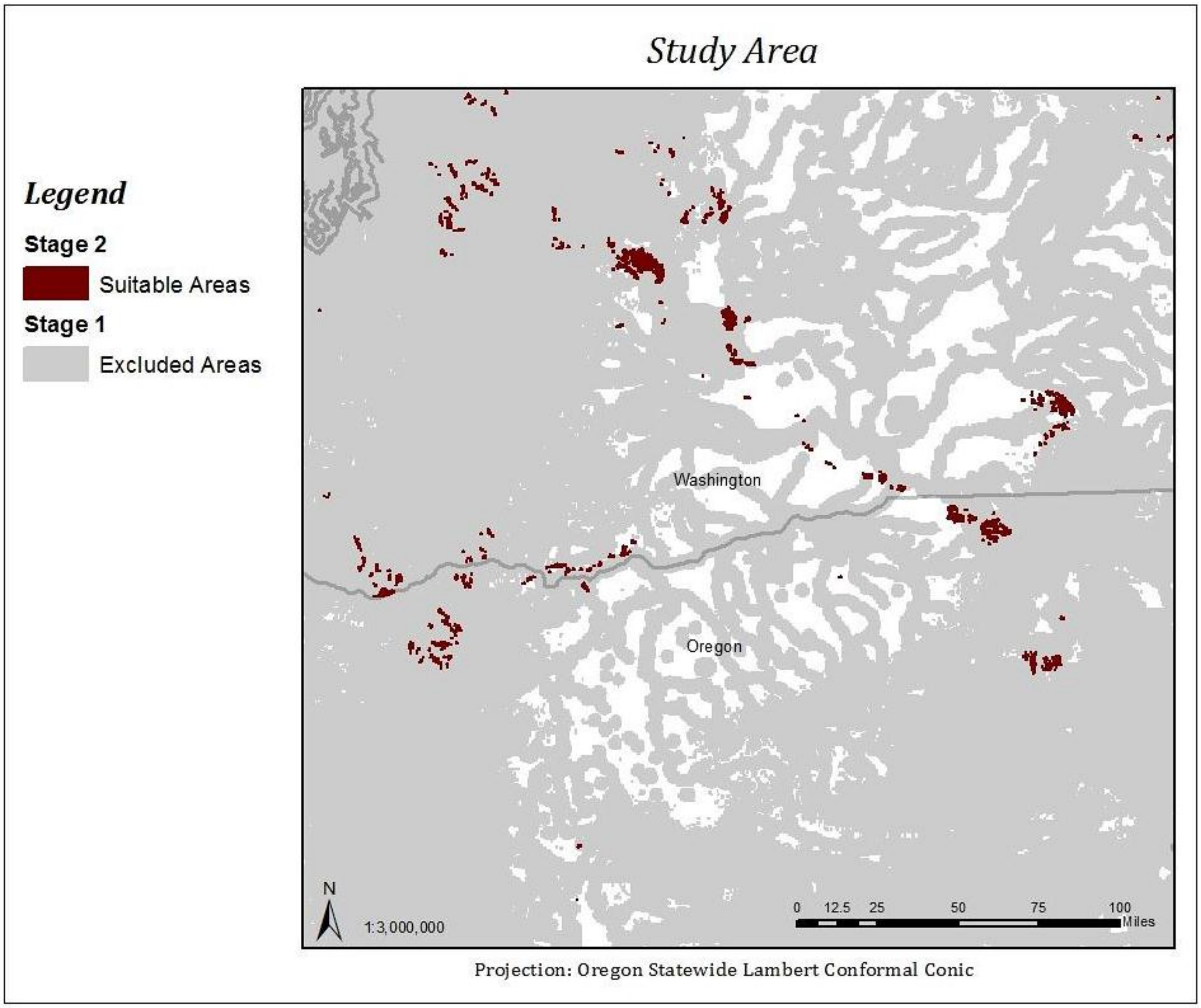

Figure 15: Map of study area showing overlay results of Stage 1 and Stage 2 analysis.

After the maps were overlaid, the next step in the Stage 3 Evaluation required identifying land units larger than 5,000 acres. The suitable raster cells were converted to polygon geometry to calculate the area, and adjacent polygons were aggregated to maximize suitable areas. A distance threshold of 1600 m (≈ 1 mile) was used for the aggregation operation, and a new layer was created from the selection of polygons > 5,000 acres. Only four polygons met this criterion and they were included in the new layer based on the AHP-derived weighted overlay.

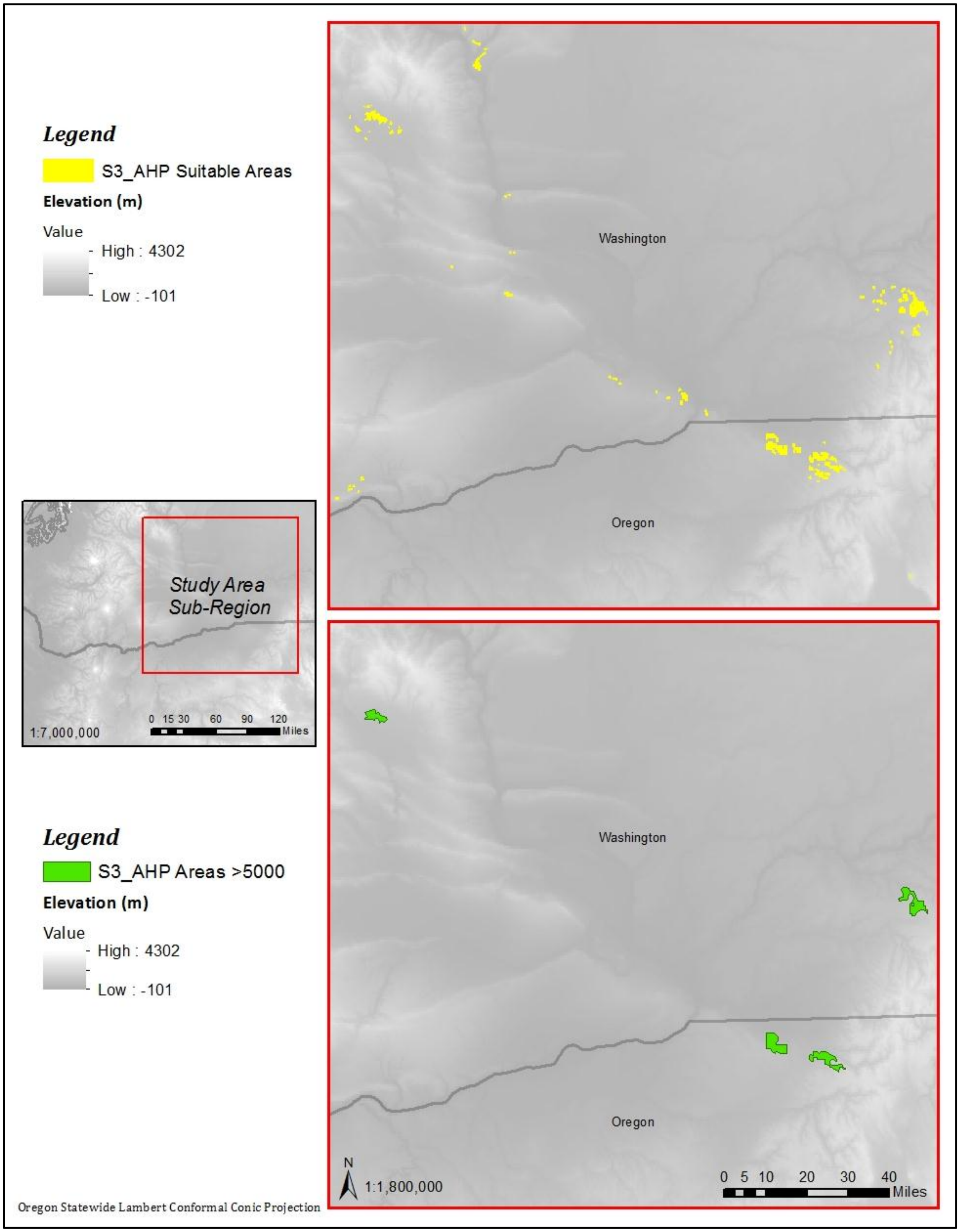

Figure 16: Maps showing the difference between all Stage 3 suitable polygons (suitability score > 0) and those polygons greater than 5,000 acres.

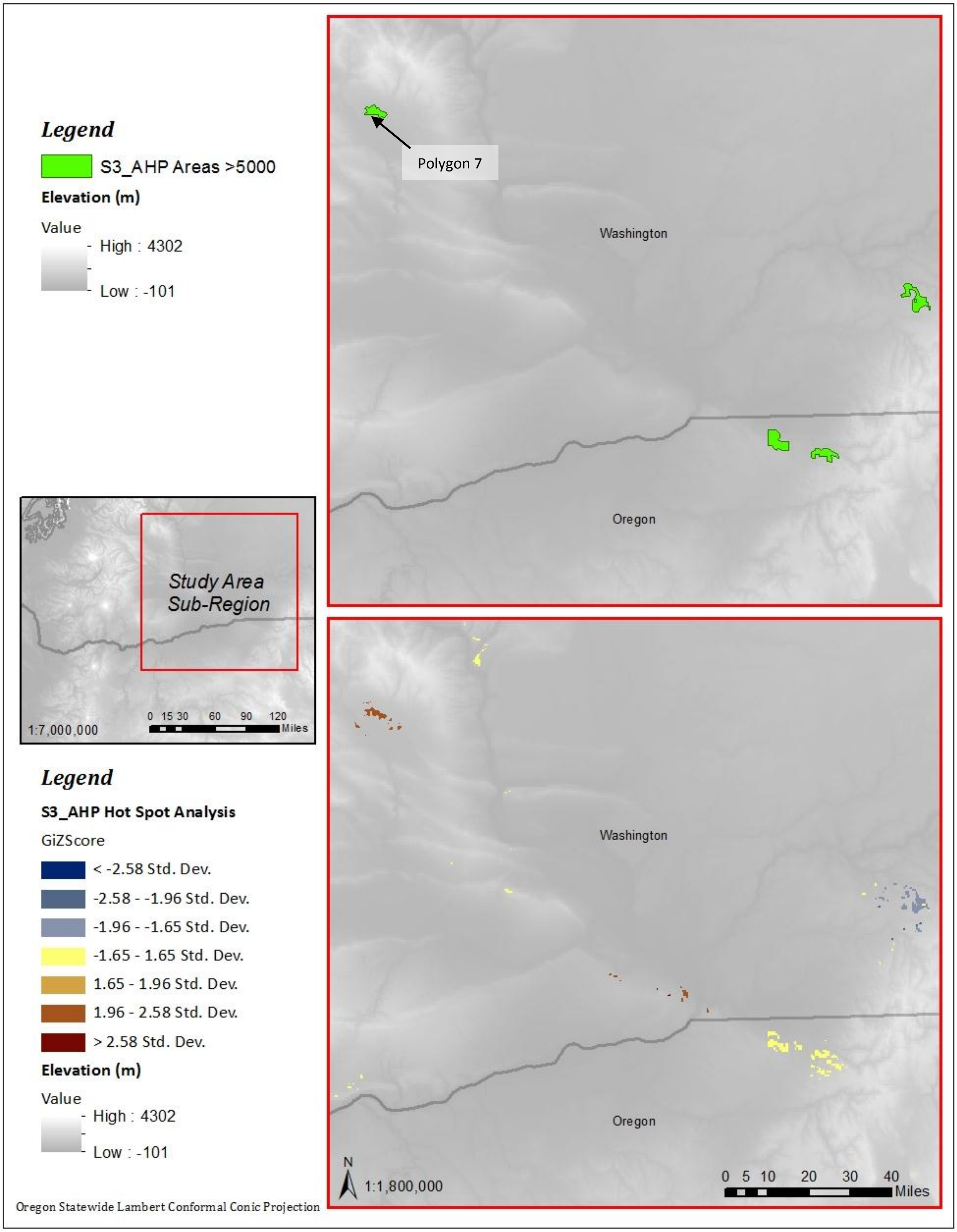

Figure 17: Maps showing the comparison between the optimal polygons and the results of the Stage 3 hot spot analysis (Getis-Ord *G*-statistic).

The four large polygons shown in the lower map in Figure 16 are the best fit for wind farm sites based on the Stage 3 Model, but running the Getis-Ord G-statistic test again can elucidate any visual correlation between these sites and areas with clusters of high values. The hot spot analysis was run again with the new set of optimal polygons, and the results are shown in Figure 17. Based on the results of this test, only the polygon in the northwest portion of the map (Polygon 7) correlates with clusters of high values, and so it would be a top candidate for further investigation into wind energy development potential in the area.

One additional map is provided in Figure 18 (below) to compare the results of the hot spot analysis with areas of high WPC and the locations of existing wind farms. This is a practical way to verify the results of the hot spot analysis and the Stage 3 Model visually, and it confirms that the optimal sites are located in highly suitable areas for wind energy development. Furthermore, the map shows that Polygon 7 is an excellent candidate based on the relative proportion of high WPC area to existing wind farms already located in that area, suggesting that this region has an abundance of untapped wind resource potential and room for growth.

Of course, the cautious optimistic may question why there are no existing wind farms in this seemingly bountiful area for wind energy, and this question rightfully deserves further investigation. One thing to consider is that Polygon 7 barely exceeded the 5,000 acre threshold, the smallest of the four (see Table 18, section 4.5), and so one could conclude that there is simply not enough suitable area to warrant massive investment in that area because there is little potential for expansion to nearby areas. Figure 19 supports this

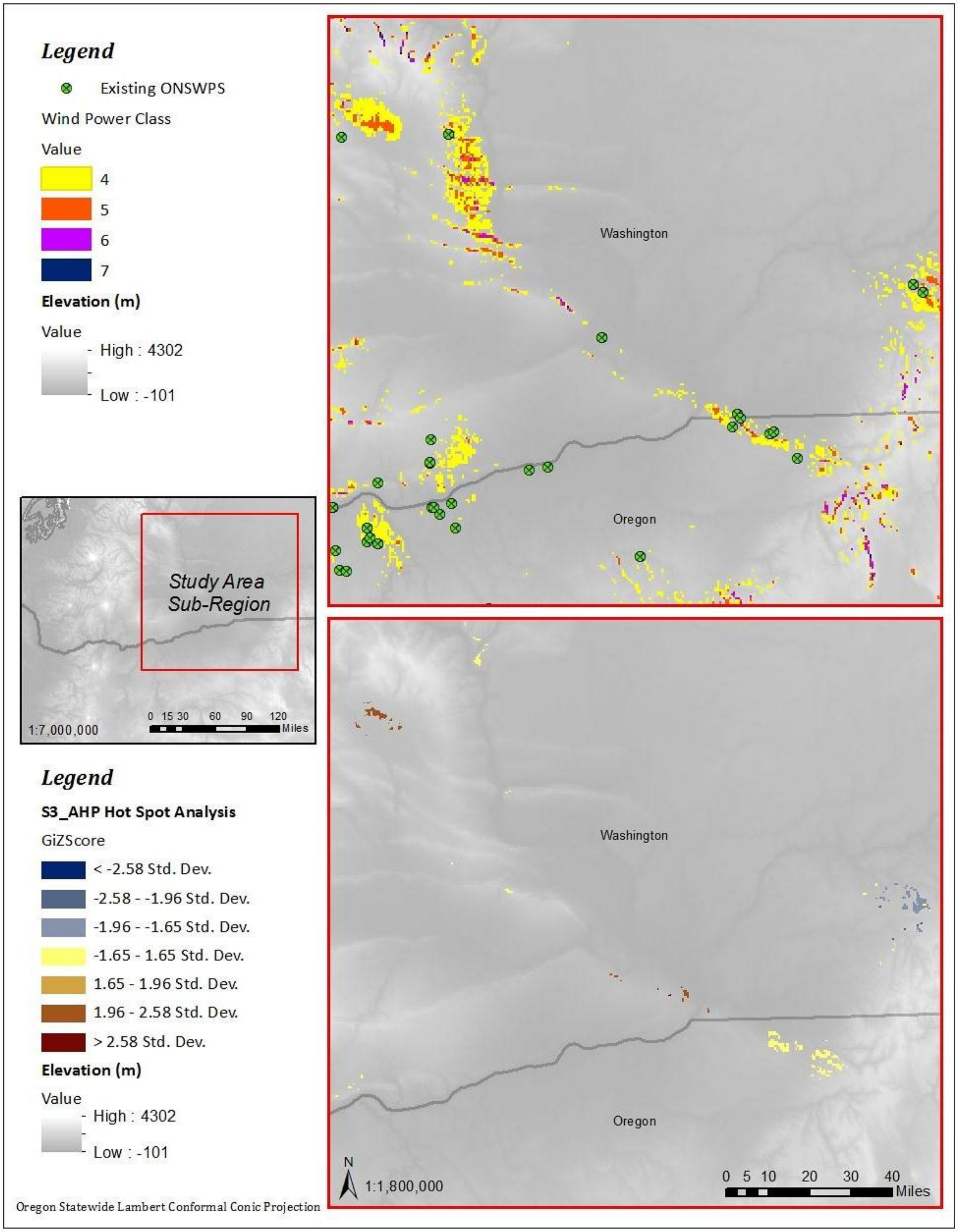

Figure 18: Maps showing the comparison between areas with high WPC and suitable area hot spots.

consideration by showing the mask used in this analysis. The mask (yellow areas) represents all areas that were not excluded due to Stage 1 constraints, and it is clear that there is not much room to expand in this area, especially compared to the other optimal polygons.

Also included in Figure 19 is a map showing the locations of cities and power lines, the next two most important criteria behind WPC, which highlights a certain disadvantage for Polygon 7 based on its proximity to nearby power lines. Compared to the other optimal polygons, which appear to have power lines running directly through them, Polygon 7 would require substantial investment to connect to the electrical grid. It is also more remote in terms of serving large populations. These factors do not preclude Polygon 7 from consideration as an optimal site; they simply demonstrate the complex nature of the spatial-MCA approach and why more detailed site-specific analysis is necessary before selecting a final site.

It is also interesting to note the location of the existing ONSWPS in relation to the suitable areas mask developed in this framework (upper map, Figure 19). In general, the existing wind farms are located within areas deemed suitable based on Stages 1 and 2 constraints, and there are several that are located within or very near the Stage 3 optimal areas. At the very least, the spatial distribution of existing ONSWPS closely mimics the spatial distribution of the suitable areas, and this affords a level of confidence in the framework and validates the model to some degree in real-world terms.

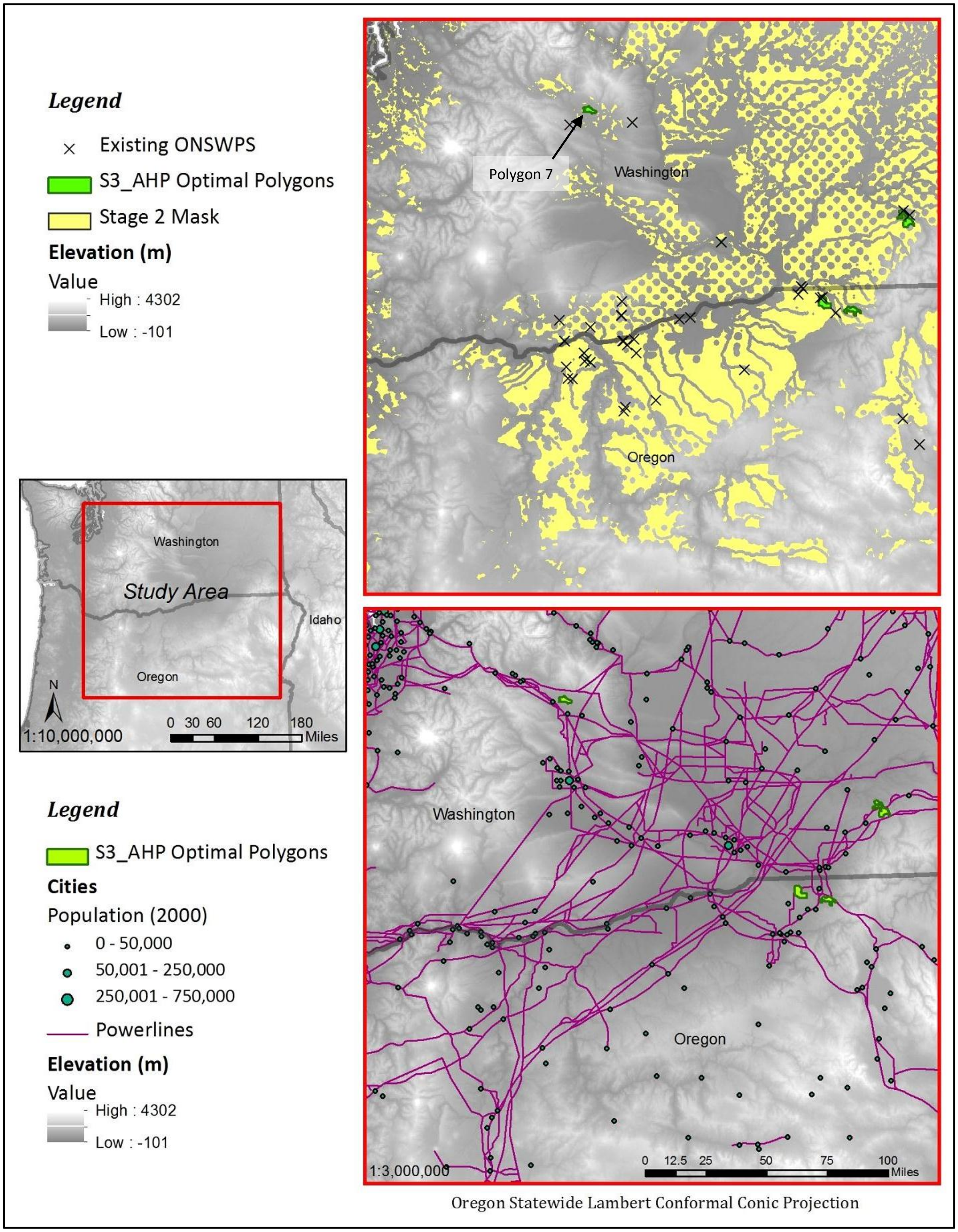

Figure 19: Maps showing the location of the optimal polygons in relation to cities, power lines, existing ONSWPS, and the Stage 2 suitable areas mask.

One additional note about the patterns observable in the Stage 2 mask (upper map, Figure 19) is the presence of what appears to be an artificially propagated series of “dots” or “holes” in the Washington portion. In fact, these holes are from the buffered wetland layer, and to some extent are artificial in the sense that the data collection methods and definition of what constitutes a wetland are manmade constructs, and as such will differ amongst departments and jurisdictions as the example of the difference between Washington and Oregon illustrates in the above figure.

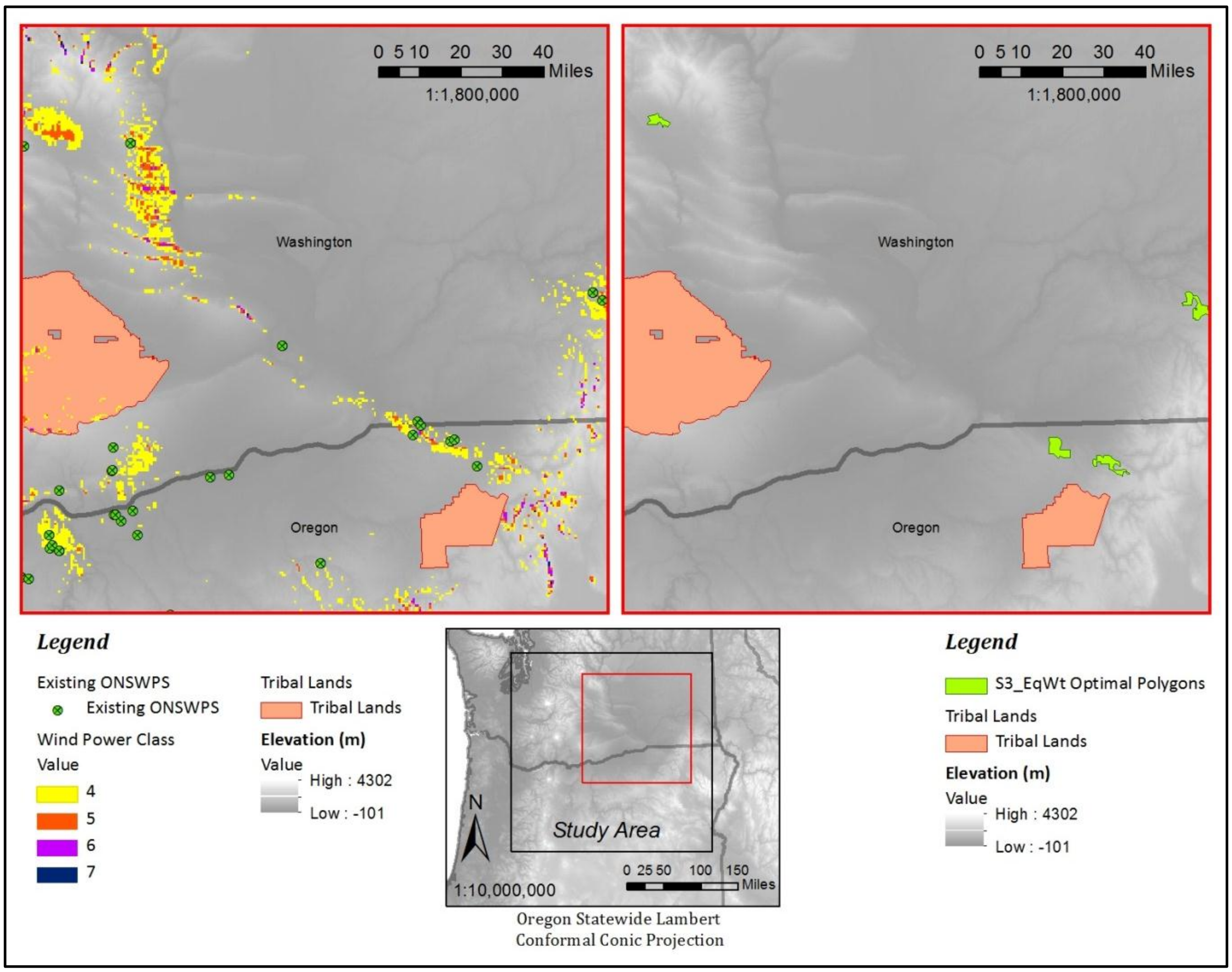

Figure 20: Maps showing locations of Tribal Lands relative to optimal sites and areas with high WPC.

The final Stage 3 criterion concerning tribal lands was also assessed at this point. However, there were no optimal sites were identified within the study area during the Stage 3 Evaluation that were located on tribal lands (Figure 20), so this criterion required no further analysis.

4.4 Suitability Assessment Discussion

As evident in Figure 19, the overwhelming majority of existing wind farms are located in areas identified by the Stage 1 and 2 models as suitable, and several wind farms exist in areas identified as optimal, which lends credence to the effectiveness of these models. However, there are a few wind farms that were not located within these areas, which was a rather unexpected result, and may be explained by the conservative nature of the constraints used in Stage 1, or perhaps these wind farms were located in areas of high WPC despite not meeting other constraints. Upon re-examination of Figure 18 (upper map), it can be seen that the latter case explains some of these anomalies, but another situation is also observable, which is that some of the wind farms are not even located in areas with high WPC. This leads to some questions about the accuracy of the WPC dataset and emphasizes the fact that potential sites must undergo thorough wind resource assessments (WRA) before pursuing development.

These cases aside, it is evident in Figure 19 that several wind farms were located within or very near optimal sites identified in the models, but also that the majority of the existing wind farms are located outside of the optimal sites. Again, this may have something to do with the inaccuracy of the WPC dataset, as WPC was the strongest selective criteria in the models, but it also suggests that wind energy siting is always a compromise and that there are limits to the predictive capacity of the models in terms of real-world results. Overall though, the sites identified as optimal by the Stage 3 Model corresponded well with the locations of existing wind farms.

Based on the results of the Stage 3 Evaluation, four optimal sites were identified, and of those four only one showed a significant clustering of high values. However, after further investigation, this site (Polygon 7, hereafter called Site D) showed some limitations to development when compared to the other three, specifically in its potential for expansion into other areas. Economies of scale are vitally important in making wind energy cost competitive with other sources of electricity, and a lack of this ability, combined with the remoteness of Site D, led to the decision to focus on Sites A-C for the Sensitivity Analysis. Since Sites A-C are also closer in proximity to one another, they can be presented in a larger-scale map. This affords the reader the ability to observe small changes in the outputs that would otherwise be impossible at the regional extent of the entire study area.

4.5 SA Results

Two different weighting schemes were implemented to measure the sensitivity of the input criteria weights. In the first scenario, equal weight was given to each of the six dynamic criteria and substituted into the Stage 2 Model *weighted overlay* tool. In the second scenario, the criteria were altered by 5% increments up to a threshold of ± 20% using the OAT method. The AHP-derived criteria weights were used as the baseline dataset for both scenarios, and the results are shown in map details of a study area sub-region for illustrative purposes. Figure 21 provides an example of the geographic distribution of suitable cells under the first scenario.

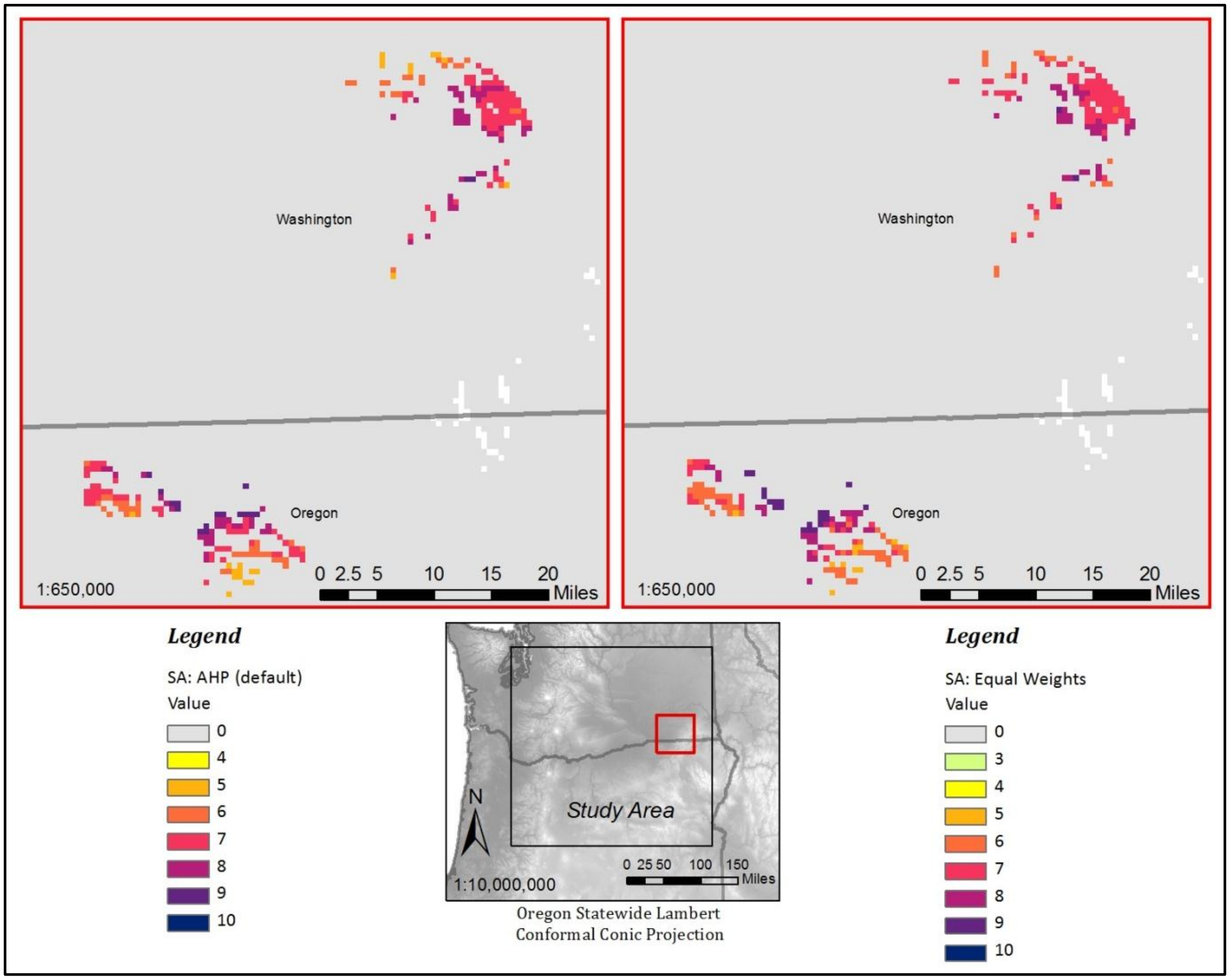

Figure 21: Visualized results of the first SA weighting scenario, showing suitable areas based on two different weighting schemes.

The map on the left shows the results of the AHP-derived input criteria weights, while the map on the right shows the output under the equally weighted scheme. The location of suitable cells is virtually identical in both maps, but the values of many cells are slightly different. A graphic illustration of the cell distribution provides a more quantifiable example of the differences (Figures 22 and 23).

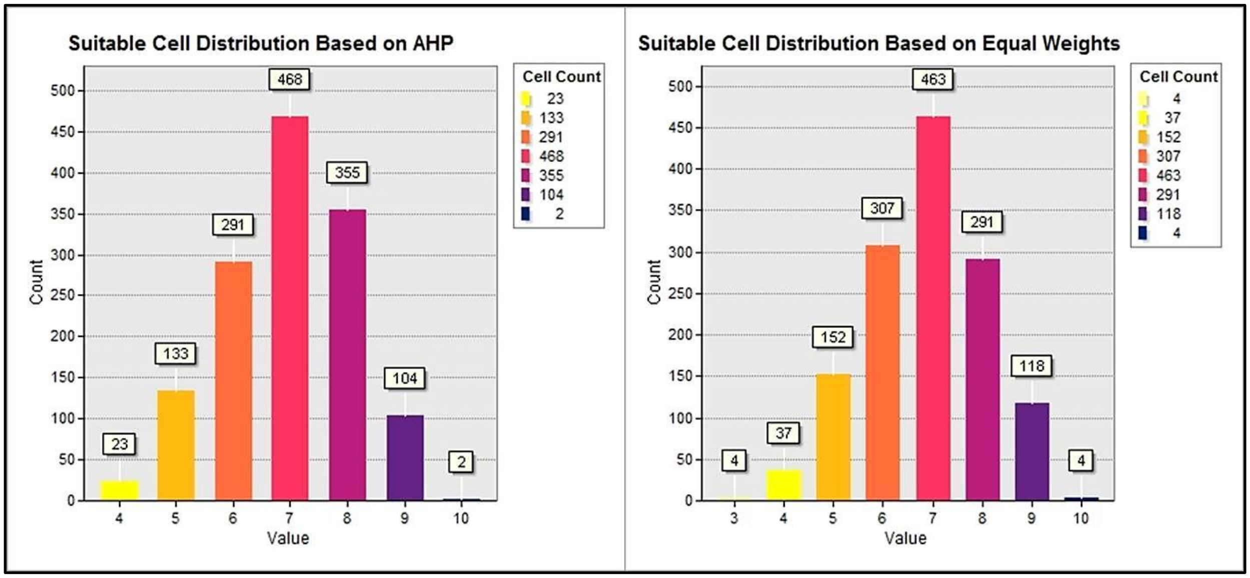

Figure 22: Histograms showing the differences in suitable cell distribution between two different weighting schemes.

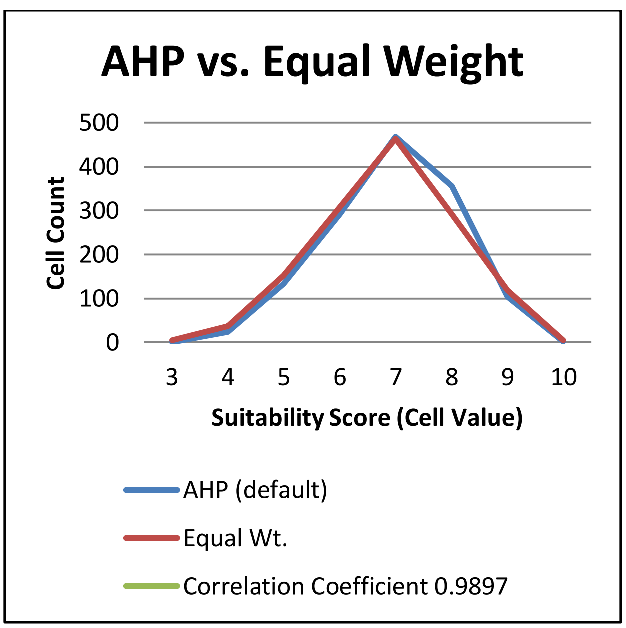

Figure 23: Line graph comparing suitable cell distribution between two weighting schemes and associated correlation coefficient.

The distributions and cell counts are similar under both weighting schemes, and although there is an additional cell value ('3') included in the equally weighted results, there are only four cells with that suitability score (Table 17). The largest difference between the two is the number of cells scored at a value of '8' (355 for AHP compared to 291 for Equal Weight), which may impact the amount of suitable acreage if one chooses to select only suitability scores ≥ 8. However, if one draws from the entire set of suitable cells, the number of total cells selected in both weighting scheme is exactly the same. In general, the AHP-based distribution is skewed slightly toward the higher values, while the Equal Weight-based cell counts represent a more classic distribution.

Table 17: Suitable cell value statistics under two weighting schemes.

Cell Value	**Cell Count**			
	AHP (default)	Equal Wt.	Standard Deviation	Avg. Deviation
3	0	4	2.828	2.00
4	23	37	9.899	7.00
5	133	152	13.435	9.50
6	291	307	11.314	8.00
7	468	463	3.536	2.50
8	355	291	45.255	32.00
9	104	118	9.899	7.00
10	2	4	1.414	1.00
SUM	1376	1376	MEAN	8.63
Correlation Coefficient		0.98974		
Average Deviation		8.57		

To find out if the difference in cell distribution had any effect on the location of optimal sites, the suitable cells were converted to polygons and then aggregated within a distance of 1,600 m (≈ 1 mile), replicating the parameters of the Stage 3 Model. Table 18 shows the difference in acreage among the four optimal polygons (larger than 5,000 acres) between the AHP-derived and the equal weighting schemes.

Table 18: Acreage statistics for optimal polygons under two different weighting schemes.

	AHP Optimal Polygons		**Equal Weight Optimal Polygons**	
Site	*Polygon ID*	*Acres*	*Polygon ID*	*Acres*
A	30	11266.5	29	11319.2
B	43	10408.3	43	10289.6
C	37	7209.1	51	9324.4
D*	7	5625.1	7	5502.1
SUM		34,509.0		36,435.3

**Not shown in figures this section.*

The differences in total acreage are slight in terms of acreage, and at the regional scale they are visually indistinguishable. Figure 24, which shows a small sub-region of the study area, reveals that the differences in Polygon ID are simply due to the numbering process used in aggregation, not that different polygons were selected in other locations. The shapes of the polygons are slightly different, but they are essentially the same sites. Neither method resulted in a consistent increase or decrease in acreage across all four sites, providing little insight into the overall impact of the input criteria weights on the output areas under the first scenario. The overall difference in acreage however suggests that the equal weighting scheme is generally less selective in terms of high cell values.

These results are also heavily influenced by the aggregation process and the 1,600 m aggregation distance. Trials were done at 400 m (one cell width) and 800 m (two cell widths), both times resulting in only one polygon larger than 5,000 acres. This seemed peculiar given the highly clustered suitable polygons, and so it was decided to use the larger aggregation distance of 1,600 m to try to maximize the number of optimal polygons without compromising the data. For preliminary analysis, this level of aggregation was considered acceptable for identifying potential development sites.

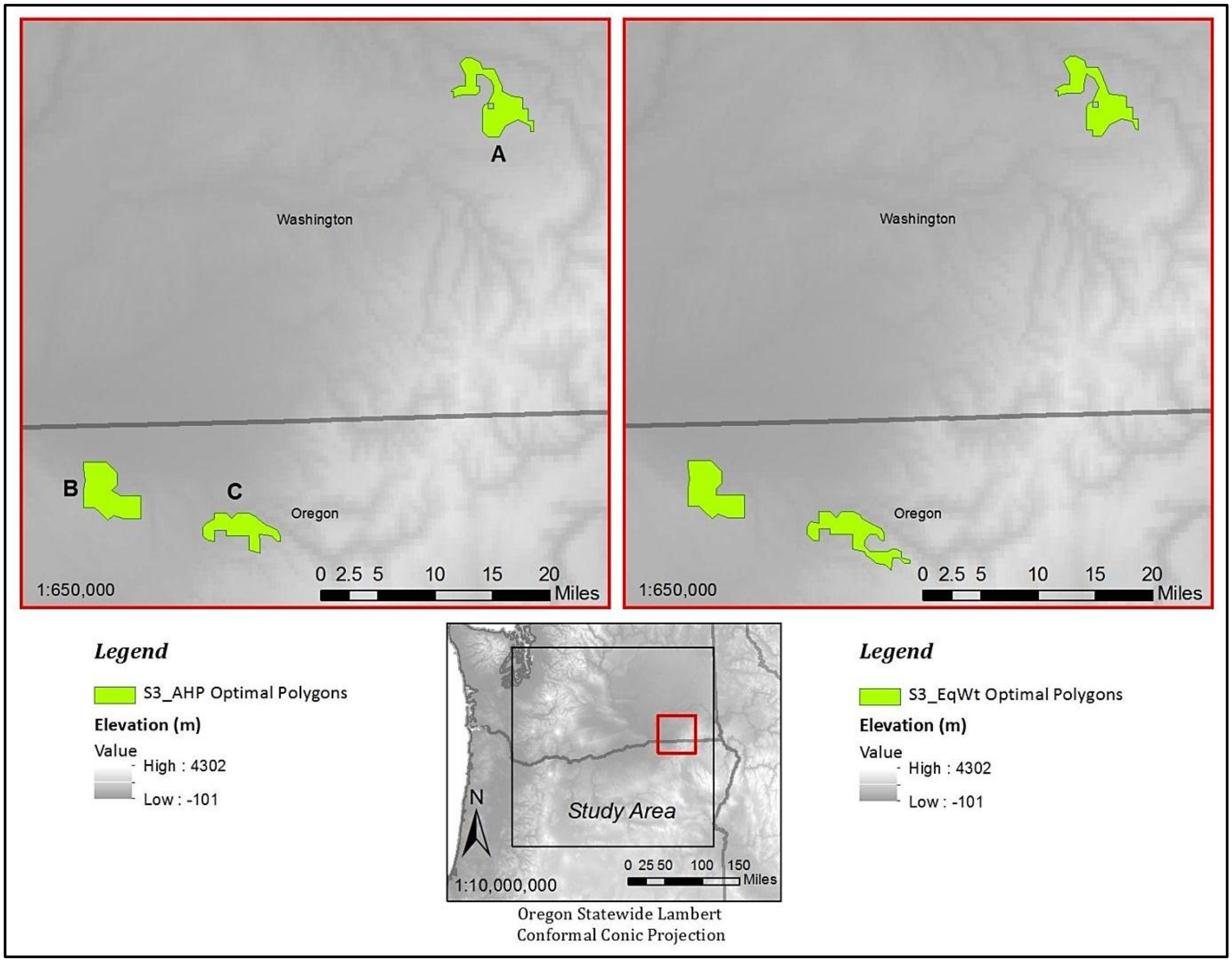

Figure 24: Map detail showing the differences in optimal polygons A, B, and C between two weighting schemes (AHP and Equal Weight).

Under the OAT scenario, the input criteria values were altered by 5% increments to a threshold of ±20% to simulate small perturbations or errors, in order to evaluate the sensitivity of the individual criteria. Table 19 shows an example of the adjusted OAT criteria values used in the weighted overlays (the complete set of OAT criteria weight tables is displayed in the Appendix). WPC and the proximity to the electrical grid (GRID) were key variables to investigate because of their large influence on the results and because they are different types of constraints; WPC suitability is based on geographic correlation, while GRID is a distance-dependent criterion. Note that the main changing criteria weights ($\boldsymbol{C_m}$) are identical for both WPC and GRID, as are the adjusted weights for the other criteria (C_i), because their AHP-derived criteria weights are identical.

Table 19: SA values for the WPC and GRID criteria using the OAT method.

	$\boldsymbol{C_m}$	C_i					
%	***WPC***	GRID	URBCITY	ROAD	LANDCOV	SLOPE	*SUM*
0.20	***0.364***	0.277	0.154	0.088	0.088	0.030	*1.000*
0.15	***0.348***	0.283	0.158	0.090	0.090	0.031	*1.000*
0.10	***0.333***	0.290	0.162	0.092	0.092	0.032	*1.000*
0.05	***0.318***	0.296	0.165	0.094	0.094	0.032	*1.000*
0.00	***0.303***	0.303	0.169	0.096	0.096	0.033	*1.000*
-0.05	***0.288***	0.310	0.173	0.098	0.098	0.034	*1.000*
-0.10	***0.273***	0.316	0.176	0.100	0.100	0.034	*1.000*
-0.15	***0.258***	0.323	0.180	0.102	0.102	0.035	*1.000*
-0.20	***0.242***	0.329	0.184	0.104	0.104	0.036	*1.000*

	$\boldsymbol{C_m}$	C_i					
%	***GRID***	URBCITY	ROAD	LANDCOV	SLOPE	WPC	*SUM*
0.20	***0.364***	0.154	0.088	0.088	0.030	0.277	*1.000*
0.15	***0.348***	0.158	0.090	0.090	0.031	0.283	*1.000*
0.10	***0.333***	0.162	0.092	0.092	0.032	0.290	*1.000*
0.05	***0.318***	0.165	0.094	0.094	0.032	0.296	*1.000*
0.00	***0.303***	0.169	0.096	0.096	0.033	0.303	*1.000*
-0.05	***0.288***	0.173	0.098	0.098	0.034	0.310	*1.000*
-0.10	***0.273***	0.176	0.100	0.100	0.034	0.316	*1.000*
-0.15	***0.258***	0.180	0.102	0.102	0.035	0.323	*1.000*
-0.20	***0.242***	0.184	0.104	0.104	0.036	0.329	*1.000*

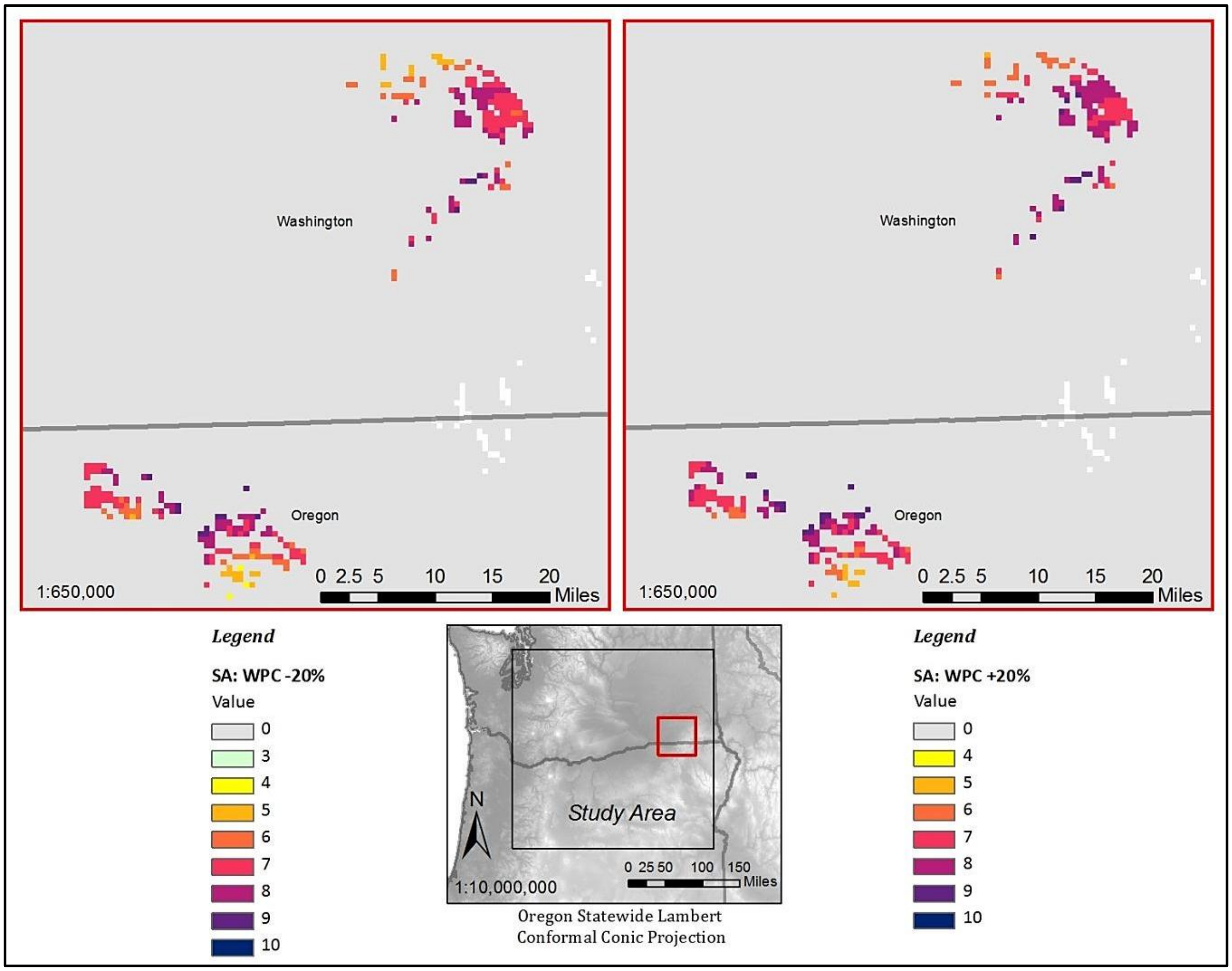

Figure 25: Maps showing the difference in suitable cell values for the WPC criterion under the OAT method (± 20%).

The visualized results of the ±20% criteria weight changes for the WPC criterion are shown in Figure 25. Again, it is difficult to comprehend the quantitative differences in suitable cell distributions from the maps, but the locations are unmistakably similar. And again the histograms (Figure 26) provide a better quantitative assessment of the differences, clearly exhibiting the skewed distribution toward higher suitability scores for the WPC +20% perturbation.

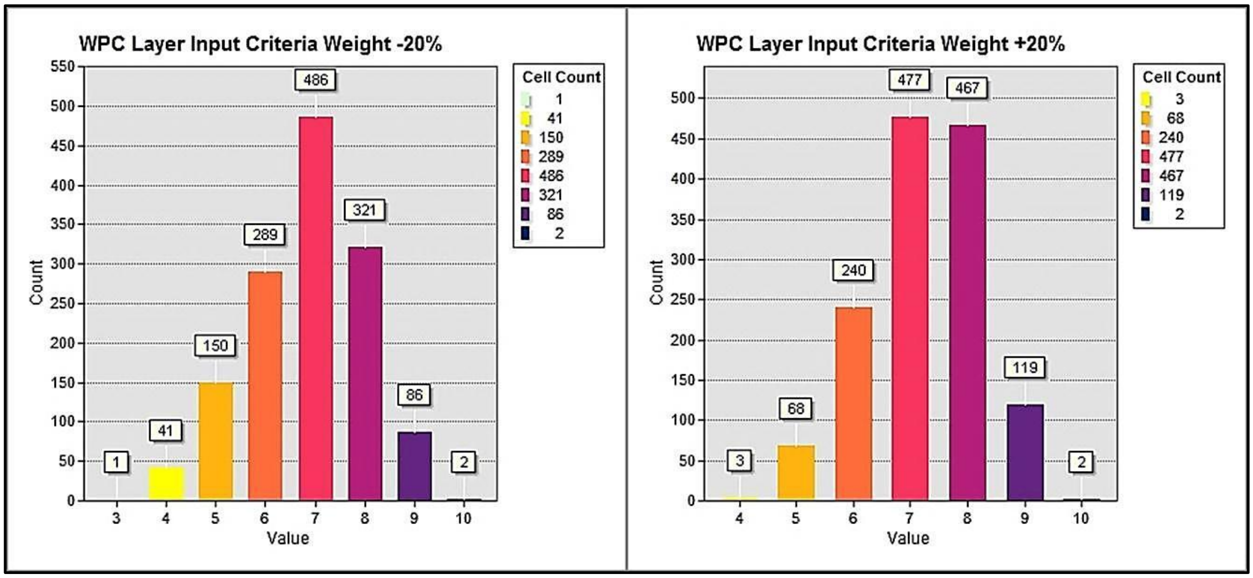

Figure 26: Histograms showing the differences in suitable cell distributions for the WPC criterion at ± 20% of the baseline values.

When combined with the AHP vs. Equal Weight distribution results, the WPC ±20% results begin to show a pattern involving the influence of WPC on the distribution of cell values. The AHP scheme, which gave WPC a 30% weight, as compared to the Equal Weight scheme which gave WPC an approximately 17% weight, has a similarly skewed distribution to that of the WPC +20% scheme, which used a 36% weight compared to 24% for the WPC -20% scheme. This suggests that the output cell values, particularly at the high end, are relatively sensitive to the input weight assigned to WPC. The correlation appears to be that the higher the input weight for the WPC criterion, the larger the number of cells with high suitability scores, specifically cells with values ≥ 8.

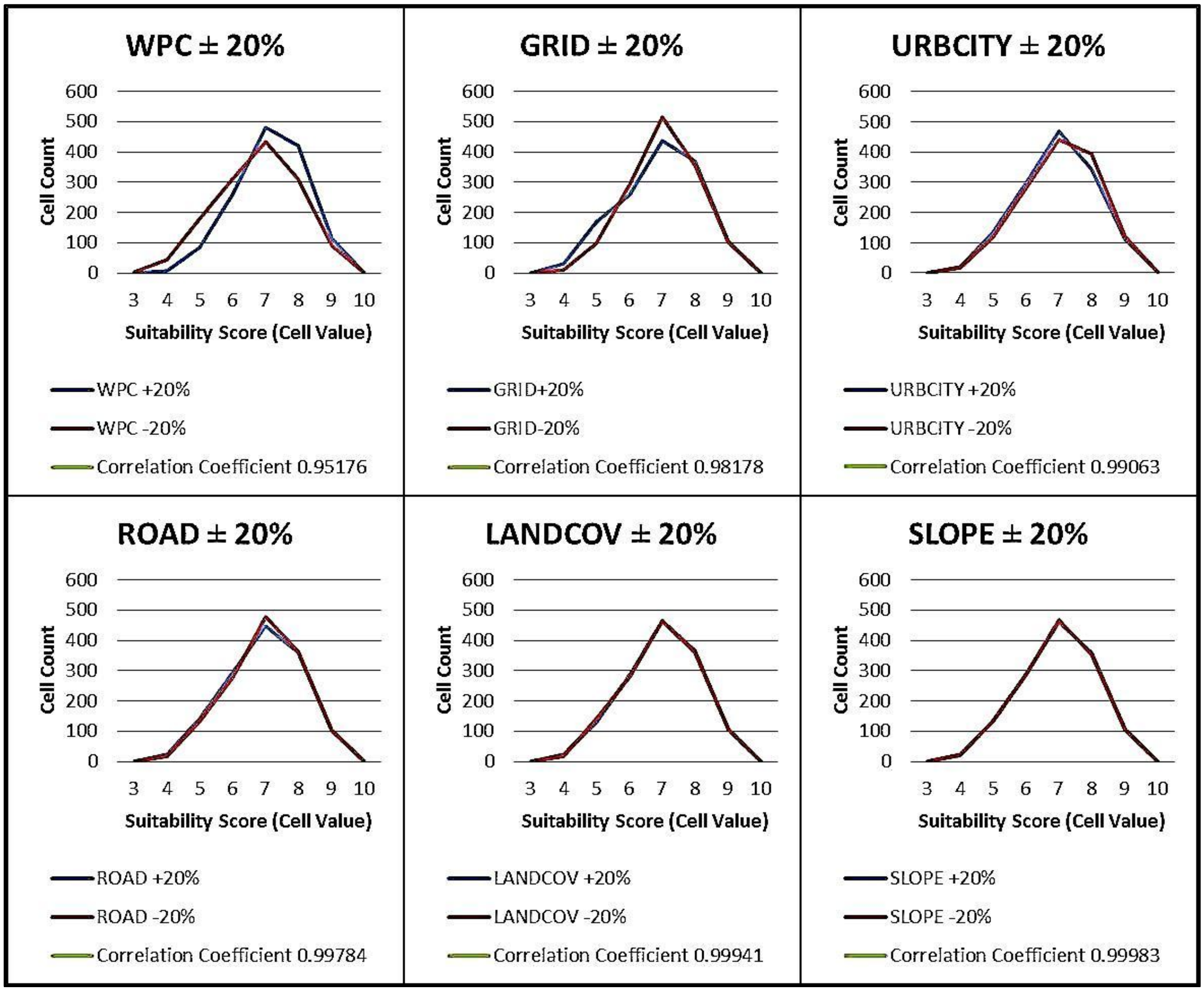

Figure 27: Line graphs showing the OAT ±20% cell distributions for the six dynamic criteria.

An interesting pattern is observable in Figure 27, with a steady increase in the correlation coefficients as the perceived importance of each variable decreases. It would be simple to assess if the AHP-derived input criteria weights descended steadily in value: the greater the input weight, the more sensitive the output is to small perturbations. However, the WPC and GRID criteria had the same AHP-derived input weights (30%), as did the ROAD and LANDCOV criteria (10%), so the relationship is not quite that straightforward. Looking at the GRID criterion may help to explain some of the variation in the output cell distributions.

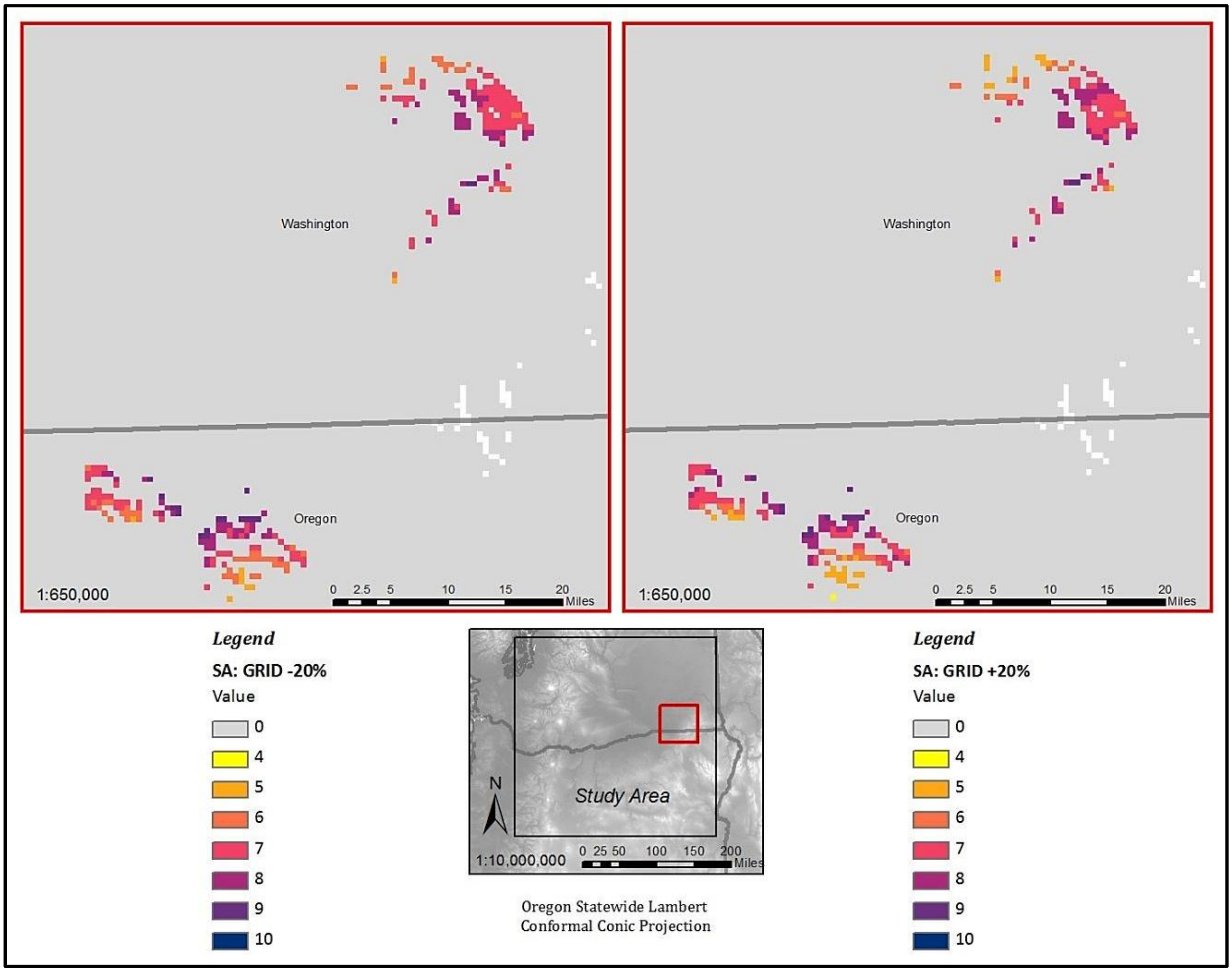

Figure 28: Maps showing the differences in suitable cell distribution for the GRID criterion under the OAT method (±20%).

Predictably, the locations of the suitable cells are the same (Figure 28), but this time the distributions are more similar as evident in the histograms in Figure 29. However, it is still difficult to visually assess the differences between the impacts of the +20% perturbations on the cell distributions for the two most influential criteria, WPC and GRID, which both had input criteria weights of 30%. A side-by-side comparison of the distributions (Figure 30) between the two layers provides a better perspective of the differences.

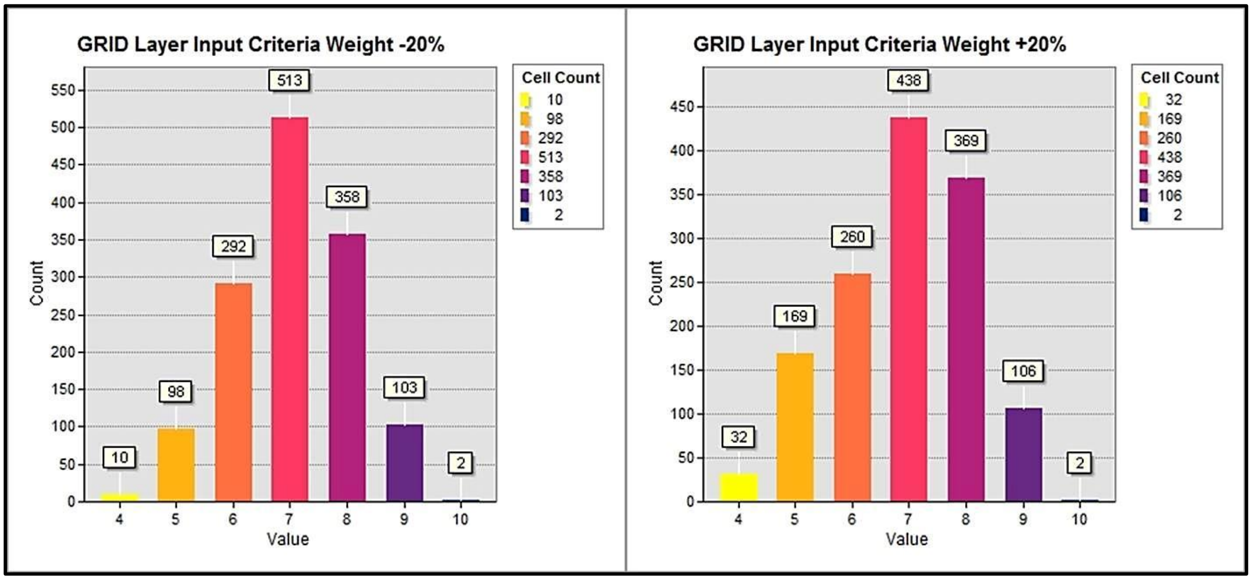

Figure 29: Histograms showing the differences in suitable cell distributions for the GRID criterion at ±20% of the baseline values.

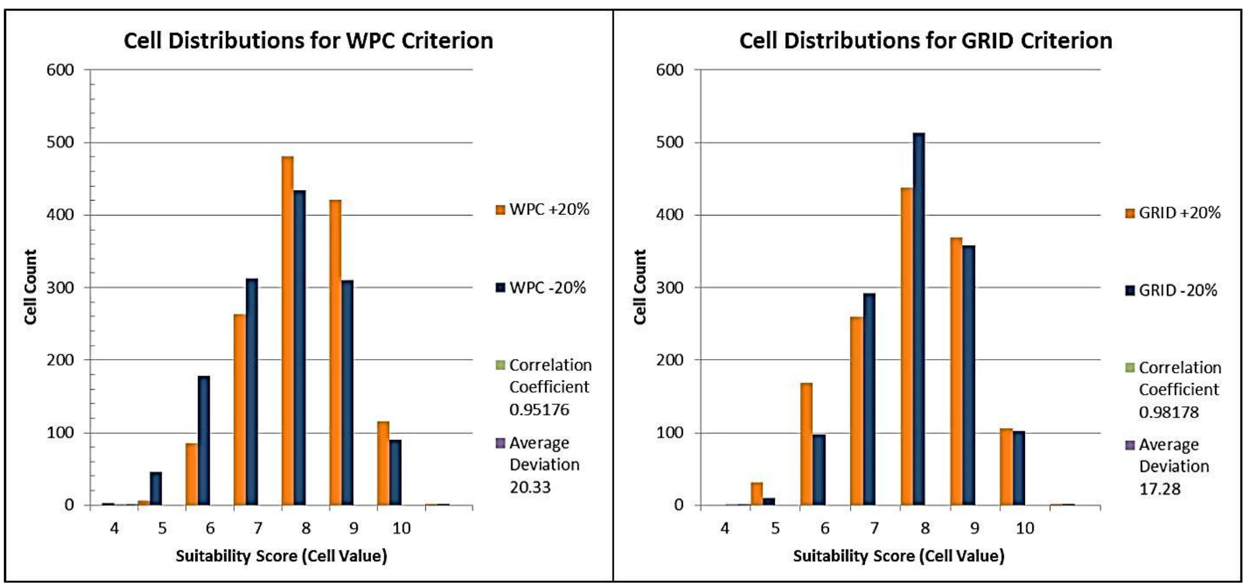

Figure 30: Histograms comparing the WPC layer and the GRID layer suitable cell distributions under the OAT weighting scheme.

Although the two layers had identical input criteria weights of 30% under the AHP scheme, and their subsequent OAT criteria weights were identical, they exhibit distinctly different distributions, and the difference in their average standard deviations is indicative of a larger pattern among all six dynamic criteria. Table 20 provides a statistical perspective of the results, and a closer examination of the average standard deviations reveals this pattern more clearly.

Table 20: Cell distribution statistics for all six dynamic criteria under the OAT weighting scheme (±20%).

Cell Value	Cell Count			
	WPC +20%	WPC -20%	Standard Deviation	Avg. Deviation
3	0	3	2.121	1.50
4	6	46	28.284	20.00
5	86	178	65.054	46.00
6	264	313	34.648	24.50
7	481	434	33.234	23.50
8	421	310	78.489	55.50
9	116	90	18.385	13.00
10	2	2	0.000	0.00
SUM	1376	1376	MEAN	23.00
Correlation Coefficient		0.95176		
Average Deviation		20.33		

Cell Value	Cell Count			
	GRID +20%	GRID -20%	Standard Deviation	Avg. Deviation
3	0	0	0.000	0.00
4	32	10	15.556	11.00
5	169	98	50.205	35.50
6	260	292	22.627	16.00
7	438	513	53.033	37.50
8	369	358	7.778	5.50
9	106	103	2.121	1.50
10	2	2	0.000	0.00
SUM	1376	1376	MEAN	13.38
Correlation Coefficient		0.98178		
Average Deviation		17.28		

Cell Value	Cell Count			
	URBCITY +20%	URBCITY -20%	Standard Deviation	Avg. Deviation
3	0	0	0.00000	0.00
4	19	16	2.12132	1.50
5	133	118	10.60660	7.50
6	299	282	12.02082	8.50
7	469	441	19.79899	14.00
8	343	395	36.76955	26.00
9	110	122	8.48528	6.00
10	3	2	0.70711	0.50
SUM	1376	1376	MEAN	8.00
Correlation Coefficient		0.99063		
Average Deviation		8.66		

Cell Value	Cell Count			
	ROAD +20%	ROAD -20%	Standard Deviation	Avg. Deviation
3	0	0	0.00000	0.00
4	24	18	4.24264	4.24
5	143	133	7.07107	7.07
6	295	279	11.31371	11.31
7	447	477	21.21320	21.21
8	361	364	2.12132	2.12
9	104	103	0.70711	0.71
10	2	2	0.00000	0.00
SUM	1376	1376	MEAN	5.83
Correlation Coefficient		0.99784		
Average Deviation		5.52		

Cell Value	Cell Count			
	LANDCOV +20%	LANDCOV -20%	Standard Deviation	Avg. Deviation
3	0	0	0.00000	0.00
4	23	18	3.53553	3.54
5	130	143	9.19239	9.19
6	285	281	2.82843	2.83
7	465	463	1.41421	1.41
8	367	360	4.94975	4.95
9	104	109	3.53553	3.54
10	2	2	0.00000	0.00
SUM	1376	1376	MEAN	3.18
Correlation Coefficient		0.99941		
Average Deviation		2.12		

Cell Value	Cell Count			
	SLOPE +20%	SLOPE -20%	Standard Deviation	Avg. Deviation
3	0	0	0.00000	0.00
4	21	23	1.41421	1.41
5	135	133	1.41421	1.41
6	291	291	0.00000	0.00
7	461	468	4.94975	4.95
8	359	355	2.82843	2.83
9	107	104	2.12132	2.12
10	2	2	0.00000	0.00
SUM	1376	1376	MEAN	1.59
Correlation Coefficient		0.99983		
Average Deviation		1.28		

4.6 SA Discussion

Comparing the equal weighting scheme to the baseline (AHP-derived) weighting scheme provided little insight into the sensitivity of the criteria weights to changes in input values. The equal weighting scheme, which altered several of the input criteria weights considerably, exemplified a nearly perfect distribution of suitable cells, while the AHP-derived weighting scheme showed a slight inclination towards higher suitable cell values. This was likely due to a correlation between the larger influence of the WPC criterion under the AHP weighting scheme. In both cases, the distributions were similar enough that no significant difference in the selection of optimal areas resulted.

Under the OAT scenario there were some interesting patterns observable, with the influence of the WPC layer being the predominant factor in the differences in cell distributions. Despite having identical input criteria weights, the WPC layer and the GIRD layer had substantially different distributions under the ±20% variations. The WPC criterion showed a larger average standard deviation and a smaller correlation coefficient when isolated compared to the GRID criterion, but the defining indicator was that an increase in the selection of higher cell values was seen under both scenarios whenever there was an increase in the WPC criterion weight (Figure 30). However, this was not the case when the situation was reversed, as the GRID criterion actually showed more of a prevalence for selecting higher cell values when the GRID criterion weight was -20% (this meant that the WPC criterion weight was subsequently increased).

While it is natural for the criteria with large influences to be the most sensitive to perturbations, this example comparing the WPC and GRID criteria, especially when combined with the results of the AHP vs. the equal-weighting scheme results, indicates that the WPC layer is the most sensitive to small perturbations in input criteria weights, and therefore has the most impact on the distribution of suitable cells.

CHAPTER FIVE: CONCLUSIONS

5.1 General Conclusions

The framework developed in this thesis successfully identified areas suitable for wind energy development based on a thorough set of criteria and three stages of evaluation, resulting in the selection of four optimal sites. The GIS models developed within this framework proved to be effective at handling the various types of data necessary for the analysis, and they can be adapted to other situations or study areas. The maps created here contain an abundance of information about the suitability of particular areas for wind energy development, and the AHP-MCA methodology employed in this framework is robust, quantifiable, and defendable.

The importance of criteria selection and constraint determination in site suitability studies cannot be emphasized enough; these processes are arguably more important than the methodology itself. The more comprehensive the set of criteria constraints used in the preliminary analysis, the more likely the project will be to avoid costly setbacks and unnecessary resource allocation during the site search process. While detailed economic analysis is a necessary part of the site search and is included in some preliminary site suitability studies, this thesis advocates an approach that postpones this type of analysis until a set of physically feasible sites has first been identified.

It is the opinion of this author that too many studies, papers, and reports are overly liberal with their assessment of developable area for wind energy. One of the primary causes of this is an incomplete set of criteria. Most studies assess site suitability by volume, how many acres can be developed, rather than the quality of developable areas. Perhaps there are incentives in place for "finding" more acreage to develop, but does it really help planners and developers if they have to sift through unfit sites that could have been eliminated during preliminary analysis? Even those who unabashedly support wind energy acknowledge the limits on productive land area, as wind energy requires massive continuous tracts of land and special atmospheric conditions. This thesis has attempted to be conservative with its assessments of suitable areas for wind energy development by being more selective, including more criteria, and excluding more area in order to identify the most optimal sites, versus just finding the most sites.

Studies that use liberal constraints or limited sets of criteria, and therefore identify a perhaps disproportionate amount of suitable land area, inherently find that all the existing wind energy developments are located within the areas that they have identified as suitable, and they may use that as evidence that their approach is effective. It is like saying that all areas on the surface of the Earth that meet the criterion of being a water body are suitable for sailing a boat. Several studies throughout the literature did not even include the proximity to the electrical transmission grid as a criterion, which is clearly an ineffective approach. This thesis hopes to provide support for the notion that less is more, in terms of quantity vs. quality, and that taking the necessary precautions and evaluating more thoroughly the relevant criteria and constraints at the preliminary stage is a beneficial approach to the site selection process.

5.2 Technical Conclusions

Chen et al. (2010) suggest that there is a lack of SA in spatial MCA approaches in the literature, and they assert that, where SA is conducted on the criteria input weights as opposed to the input values, weight sensitivity should be visualized geographically when possible. In other words, there is a lack of appropriate *spatial* analysis in the arena of GIS-MCA site suitability approaches. In fact, of the four studies reviewed in this thesis, only one study even presented a visualization of the SA results (in Tegou et al., 2010). This ratio seems to be consistent, if not generous, throughout the literature, and it highlights an area where the visualization capabilities of GIS can be exemplified to great effect.

This thesis has attempted to address this criticism in two ways: first through a cartographic presentation of the results, which provide a substantial amount of information through the visual medium that is unique to maps, and second through the use of distribution graphs and tables that provide a quantitative, while still visual, view of the results, creating a bridge between numbers/values and their respective locations in space.

This combination of approaches demonstrates the versatility and effectiveness of GIS software packages to evaluate such complex decision-making tasks, and it provides a robust set of results on which to base those decisions. Spatial SA has proved to be a powerful tool for identifying patterns and establishing a considerable level of confidence in the results. It has also provided a means of assessing the capabilities and limits of the models developed here.

The accurate estimation of criteria weights is imperative for spatial analysis overlay approaches. The results from this analysis show that the perceived importance (input weight) of the criteria have a substantial impact on the suitable cell distributions of a selected area, and the effects of small perturbations (±20% of the baseline values) increase as the criteria weight increases (Figure 27). In most cases, these effects were relatively small, but this pattern suggests that if a criterion is assigned a very large input weight then the effects of small perturbations would have a significant impact on the cell distribution.

This highlights the benefits of using the AHP to derive input criteria weights. The AHP provides a means of ranking the importance of diverse criteria on a common scale (i.e. the ability to compare "apples and oranges") and therefore delivers a more accurate approximation of their influence on the final outcome. The results of this analysis showed that the AHP-based weighting scheme was more selective in terms of identifying suitable land area (Table 18) and it selected areas with higher suitability scores (Table 17; Figures 22 and 23) when compared to the outputs under the equal weighting scheme.

However, the results are not overwhelmingly significant in favor of the AHP outputs, and one may question whether it is worth going through all the trouble to use the AHP when the equal weighting scheme produced visually similar results. One reason for this similarity is due to the Stage 1 excluded areas and the subsequent mask used in Stage 2, which left very little land area to examine (Table 18), which is why the cell counts were identical. It is likely that the two methods would yield remarkably different cell counts if the remaining land area wasn't limited by the excluded areas mask.

Another factor to consider is that the AHP-derived input criteria weights were relatively similar in this case, ranging from 30% to 3%, while the Equal Weights scheme assigned an approximately 17% weight to all six criteria. When altered by ±20%, many of the criteria were within a few percentage points of one another (Figures A-F, Appendix), with many near 17%, so this study may not be a great example of the effectiveness of AHP over a uniform weighting scheme. Nevertheless, the AHP did show improved results and one could expect it to be considerably more accurate if applied to a situation where the input criteria weights were more widely varied, for example ranging from 60% to 3%.

In addition, the AHP is mathematically defensible, and if the results were being measured purely in mathematical terms, rather than spatial distributions, one could calculate a clear-cut best option or set of best options. This could also be possible with these results if one were to calculate the overall suitability scores for each of the optimal sites, and this is one area where this methodology could be expanded. A more detailed assessment of the differences between the AHP outputs and the equally weighted outputs would improve the confidence in these results as well, such as applying the ±20% OAT approach to the equally weighted criteria and conducting the Stage 3 analysis and the SA on the entire study area without being limited by the excluded areas mask.

Another important conclusion from this project is that the data conversion and organization process is critical to the success of the analysis. Acquiring the necessary datasets is obviously important as well, but taking the time to convert the datasets into common formats saves many headaches later in the analysis. Also, with the inclusion of a large set of input criteria, the number of data layers in the GIS can get out of hand quite easily, so organization is another key. This thesis employed an ArcGIS file geodatabase to organize the data, which handles much of the data management automatically and enforces some basic consistency among the datasets used in the analysis.

One of the primary features that the geodatabase manages is the cell size of raster datasets. This framework used two different cell sizes during the project: 798 m during the data conversion process and 400 m during the construction of the models and subsequent analysis. It is unclear exactly what type of impact this may have had on the analysis results, but in terms of balancing time-savings with the accuracy of the results, the chosen cell sizes seemed acceptable for preliminary regional analysis. However, a more consistent approach may improve the accuracy of the results.

Another way that this framework might be improved is through the use of fuzzy sets for defining categorical membership. While Boolean logic is simple to use and to understand, it is this simplicity that is invariably problematic for complex multi-criteria analysis where many shades of gray exist. Studies in recent years have explored the use of fuzzy measures for wind farm siting using MCA-GIS approaches and found this approach has many benefits over Boolean overlay, weighted summation, or weighted linear combination (WLC) approaches (Boroushaki & Malczewski, 2008; Hansen, 2005; Jiang & Eastman, 2000). Of course, adding this type of complexity to an already complex process may be a more academic endeavor than many planners and developers wish to engage in, but it certainly has the potential to improve the accuracy of the results and, most importantly, provide a stronger level of confidence in the decisions.

AHP is an excellent means of ensuring consistency in the decision-making process, but it has its limits, too. There are many sources of criticism throughout the literature describing the shortcomings of AHP, most of which concern the advanced mathematics and theories involved, but one of the limitations relates to the use of fuzzy set theory. Boroushaki and Malczewski (2008) point out that the AHP is limited in its linguistic ability for describing quantities (i.e. "few," "many," "one," etc.), and they propose that a combination of AHP with ordered weight averaging (OWA) methods, which include linguistic quantifiers, could expand the range of decision strategies available using fuzzy logic.

Another limitation of the AHP is the possibility of a paradoxical situation where the decision-maker has created a pairwise matrix to the best of their ability, but still fails the consistency test (Karapetrovic & Rosenbloom, 1999). This could easily happen when there are large numbers of decision makers with widely varying levels of background knowledge and expertise, as in RES site selection processes. Karapetrovic and Rosenbloom (1999) suggest adding quality control approach to the AHP consistency check, and although it would not apply directly to this study, it may be a beneficial element to add to the methodology when trying to adapt it to other areas or situations.

As the methodology exists now, I believe it could be applied in other areas reasonably well, particularly those with similar socio-economic status and political goals. There are aspects to RES siting that are inherently specific to local and/or regional legislation surrounding development, and traditional supply/demand models do not consistently apply when massive government subsidies are present, so it highly improbable that any universal model could ever be developed that would effectively apply in every situation. These types of pressures largely relate to the criteria addressed in Stage 1, and could be adjusted with minor effort. However, the strength of this framework is that the Stage 2 dynamic criteria, which are primarily physical (or geographical), and thus generally avoid legislative trappings, are widely adaptable to any region for preliminary analysis.

5.3 Future Work

One natural area to expand the work presented in this thesis is to evaluate the economic costs, benefits, and risks associated with developing the selected sites. Several approaches are evident at varying levels of detail in the literature, and despite their limited ability to accurately portray development costs, these approaches can provide valuable information and another means of evaluating potential sites. One approach that has particular appeal for this type of analysis is presented by Lee et al. (2009). It combines AHP with benefits, opportunities, costs, and risks (BOCR), and may fit well within the scope of preliminary analysis without getting too site-specific.

A second extension of this research, which is of personal interest, would be to integrate GIS-based learning modules into the education system in order to investigate the hypothesis that *spatial thinking, through the application of spatial science theory and GIS technology, improves overall student performance, particularly in math and science*. A recent emphasis on improving math and science performance in the U.S. has led to the implementation of increasingly popular "place-based" education initiatives and new national Science, Technology, Engineering, and Math (STEM) Education standards (Kuenzi, Matthews, & Mangan, 2006; The White House, 2011).

The education system is an arena that stands to benefit from an infusion of spatial thinking and spatial problem solving technology, especially if it can be found to improve overall student performance. Using the example of ONSWPS site selection, I would eventually like to implement this tool into such learning modules as an example of spatial problem solving using GIS. The motivation to implement the tool developed in this thesis into course modules has informed the design of this project and its outcomes to some degree, and I believe this would be a tremendous opportunity to expand and strengthen the role of GIS in students' lives and promote spatial literacy in the public arena.

Another way in which this research could have a greater impact on the public is through the production of interactive, web-based maps. Web-based mapping applications have been developed for wind energy siting and show serious potential for improving information dissemination and increasing public participation (Berry, Higgs, Fry, & Langford, 2011; Bishop & Stock, 2010; Jankowski, 2009; Simao, Densham, & Haklay, 2009).

At the very least, the publication of these suitability maps online, such as through the ArcGIS Online interface, could provide a heightened level of access to this information for planners, decision makers, politicians, students, and the general public. Improving access to this type of information will be increasingly important as suitable land area is reduced through urban sprawl and competing wind energy development, and as renewable energy sources are mandated to become a larger percentage of the energy mix in the near future due to renewable portfolio standards and pressures to move away from fossil fuel-based sources of electricity generation. If the United States is going to achieve its goal of 20% wind energy by the year 2030 (U.S. Department of Energy, 2008), tools like this will play a substantial role in effectively finding optimal sites for wind energy development, and the information presented here and in similar studies will be invaluable for educating people about the complex issues involved in finding the best sites.

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APPENDIX

Table 21: Criteria weights for the WPC layer OAT analysis

	C_m	C_i					
%	***WPC***	GRID	URBCITY	ROAD	LANDCOV	SLOPE	*SUM*
0.20	***0.364***	0.277	0.154	0.088	0.088	0.030	*1.000*
0.15	***0.348***	0.283	0.158	0.090	0.090	0.031	*1.000*
0.10	***0.333***	0.290	0.162	0.092	0.092	0.032	*1.000*
0.05	***0.318***	0.296	0.165	0.094	0.094	0.032	*1.000*
0.00	***0.303***	0.303	0.169	0.096	0.096	0.033	*1.000*
-0.05	***0.288***	0.310	0.173	0.098	0.098	0.034	*1.000*
-0.10	***0.273***	0.316	0.176	0.100	0.100	0.034	*1.000*
-0.15	***0.258***	0.323	0.180	0.102	0.102	0.035	*1.000*
-0.20	***0.242***	0.329	0.184	0.104	0.104	0.036	*1.000*

Table 22: Criteria weights for the GRID layer OAT analysis.

	C_m	C_i					
%	***GRID***	URBCITY	ROAD	LANDCOV	SLOPE	WPC	*SUM*
0.20	***0.364***	0.154	0.088	0.088	0.030	0.277	*1.000*
0.15	***0.348***	0.158	0.090	0.090	0.031	0.283	*1.000*
0.10	***0.333***	0.162	0.092	0.092	0.032	0.290	*1.000*
0.05	***0.318***	0.165	0.094	0.094	0.032	0.296	*1.000*
0.00	***0.303***	0.169	0.096	0.096	0.033	0.303	*1.000*
-0.05	***0.288***	0.173	0.098	0.098	0.034	0.310	*1.000*
-0.10	***0.273***	0.176	0.100	0.100	0.034	0.316	*1.000*
-0.15	***0.258***	0.180	0.102	0.102	0.035	0.323	*1.000*
-0.20	***0.242***	0.184	0.104	0.104	0.036	0.329	*1.000*

Table 23: Criteria weights for the URBCITY layer OAT analysis.

	C_m	C_i					
%	***URBCITY***	ROAD	LANDCOV	SLOPE	WPC	GRID	*SUM*
0.20	***0.203***	0.092	0.092	0.032	0.291	0.291	*1.000*
0.15	***0.194***	0.093	0.093	0.032	0.294	0.294	*1.000*
0.10	***0.186***	0.094	0.094	0.032	0.297	0.297	*1.000*
0.05	***0.177***	0.095	0.095	0.033	0.300	0.300	*1.000*
0.00	***0.169***	0.096	0.096	0.033	0.303	0.303	*1.000*
-0.05	***0.161***	0.097	0.097	0.033	0.306	0.306	*1.000*
-0.10	***0.152***	0.098	0.098	0.034	0.309	0.309	*1.000*
-0.15	***0.144***	0.099	0.099	0.034	0.312	0.312	*1.000*
-0.20	***0.135***	0.100	0.100	0.034	0.315	0.315	*1.000*

Table 24: Criteria weights for the ROAD layer OAT analysis.

	C_m	C_i					
%	***ROAD***	LANDCOV	SLOPE	WPC	GRID	URBCITY	*SUM*
0.20	***0.115***	0.094	0.032	0.297	0.297	0.165	*1.000*
0.15	***0.110***	0.094	0.032	0.298	0.298	0.166	*1.000*
0.10	***0.106***	0.095	0.033	0.300	0.300	0.167	*1.000*
0.05	***0.101***	0.095	0.033	0.301	0.301	0.168	*1.000*
0.00	***0.096***	0.096	0.033	0.303	0.303	0.169	*1.000*
-0.05	***0.091***	0.097	0.033	0.305	0.305	0.170	*1.000*
-0.10	***0.086***	0.097	0.033	0.306	0.306	0.171	*1.000*
-0.15	***0.082***	0.098	0.034	0.308	0.308	0.172	*1.000*
-0.20	***0.077***	0.098	0.034	0.309	0.309	0.173	*1.000*

Table 25: Criteria weights for the LANDCOV layer OAT analysis.

	C_m	C_i					
%	***LANDCOV***	SLOPE	WPC	GRID	URBCITY	ROAD	*SUM*
0.20	***0.115***	0.032	0.297	0.297	0.165	0.094	*1.000*
0.15	***0.110***	0.032	0.298	0.298	0.166	0.094	*1.000*
0.10	***0.106***	0.033	0.300	0.300	0.167	0.095	*1.000*
0.05	***0.101***	0.033	0.301	0.301	0.168	0.095	*1.000*
0.00	***0.096***	0.033	0.303	0.303	0.169	0.096	*1.000*
-0.05	***0.091***	0.033	0.305	0.305	0.170	0.097	*1.000*
-0.10	***0.086***	0.033	0.306	0.306	0.171	0.097	*1.000*
-0.15	***0.082***	0.034	0.308	0.308	0.172	0.098	*1.000*
-0.20	***0.077***	0.034	0.309	0.309	0.173	0.098	*1.000*

Table 26: Criteria weights for the SLOPE layer OAT analysis.

	C_m	C_i					
%	***SLOPE***	WPC	GRID	URBCITY	ROAD	LANDCOV	*SUM*
0.20	***0.040***	0.301	0.301	0.168	0.095	0.095	*1.000*
0.15	***0.038***	0.301	0.301	0.168	0.096	0.096	*1.000*
0.10	***0.036***	0.302	0.302	0.168	0.096	0.096	*1.000*
0.05	***0.035***	0.302	0.302	0.169	0.096	0.096	*1.000*
0.00	***0.033***	0.303	0.303	0.169	0.096	0.096	*1.000*
-0.05	***0.031***	0.304	0.304	0.169	0.096	0.096	*1.000*
-0.10	***0.030***	0.304	0.304	0.170	0.096	0.096	*1.000*
-0.15	***0.028***	0.305	0.305	0.170	0.096	0.096	*1.000*
-0.20	***0.026***	0.305	0.305	0.170	0.097	0.097	*1.000*

Table 27: Default GAP Status Code assigned by designation type, from USGS (2011).

Domain Code	Domain Description	Default GAP Status Code
National Designations		
100	National Park	2
101	National Forest-National Grassland	3
102	National Trail	4
103	National Wildlife Refuge	2
104	National Natural Landmark	2
105	National Landscape Conservation System - Non Wilderness	3
106	National Landscape Conservation System - Wilderness	2
107	Native American Land	4
Other Designations		
109	Protective Management Area - Feature	3
110	Protective Management Area - Land, Lake or River	3
111	Habitat or Species Management Area	2
112	Recreation Management Area	3
113	Resource Management Area	3
114	Wild and Scenic River	2
115	Research and Educational Land	2
116	Marine Protected Area	3
117	Wilderness Area	2
118	Area of Critical Environmental Concern	3
119	Research Natural Area	2
120	Historic / Cultural Area	3
121	Mitigation Land	3
122	Military Land	4
123	Watershed Protection Area	3
124	Access Area	4
125	Special Designation Area	3
126	Other Designation	4
127	Not Designated	4
State Designations		
300	State Park	3
301	State Forest	3
302	State Trust Lands	3
303	State Other	4
Local Government Designations		
500	Local Conservation Area	2
501	Local Recreation Area	3
502	Local Forest	3
503	Local Other	4
Private Designations		
700	Private Conservation Land	2
701	Agricultural Protection Land	3
702	Conservation Program Land	2
703	Forest Stewardship Land	3

Table 27 (Continued): GAP Status Code Definitions, from USGS (2011).

Status 1: An area having permanent protection from conversion of natural land cover and a mandated management plan in operation to maintain a natural state within which disturbance events (of natural type, frequency, intensity, and legacy) are allowed to proceed without interference or are mimicked through management.

Status 2: An area having permanent protection from conversion of natural land cover and a mandated management plan in operation to maintain a primarily natural state, but which may receive uses or management practices that degrade the quality of existing natural communities, including suppression of natural disturbance.

Status 3: An area having permanent protection from conversion of natural land cover for the majority of the area, but subject to extractive uses of either a broad, low-intensity type (e.g., logging, OHV recreation) or localized intense type (e.g., mining). It also confers protection to federally listed endangered and threatened species throughout the area.

Status 4: There are no known public or private institutional mandates or legally recognized easements or deed restrictions held by the managing entity to prevent conversion of natural habitat types to anthropogenic habitat types. The area generally allows conversion to unnatural land cover throughout or management intent is unknown.

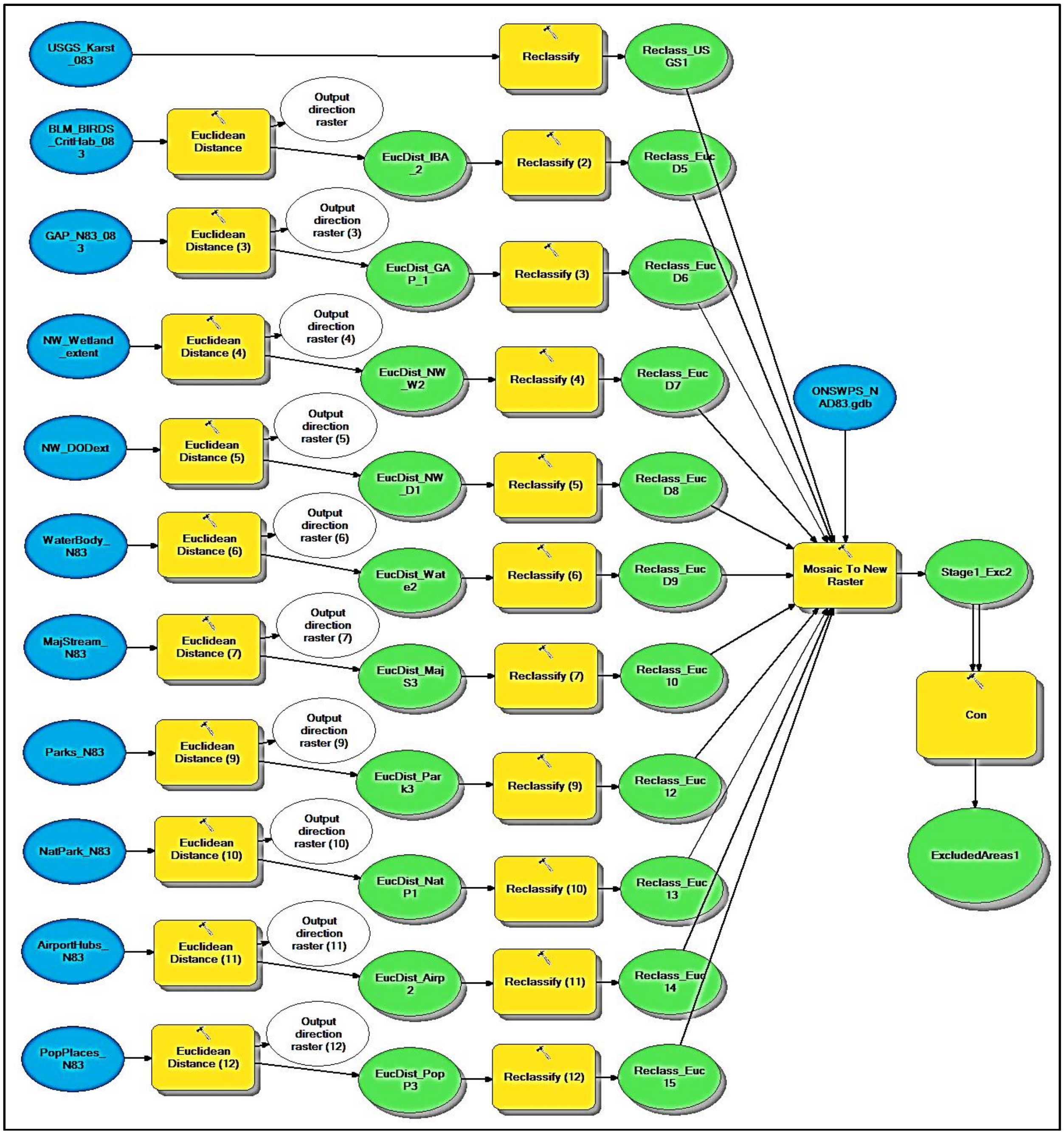

Figure 31: Schematic of the Stage 1 Model built using ArcGIS ModelBuilder.

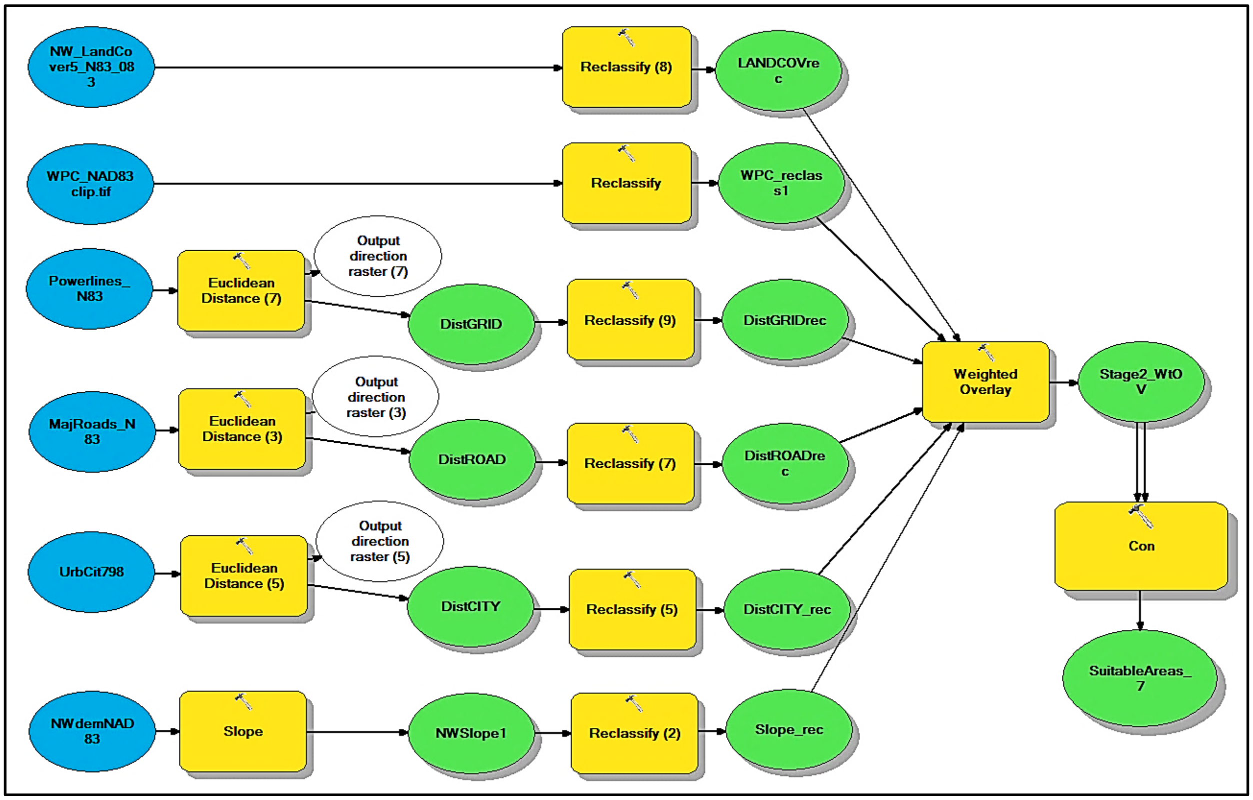

Figure 32: Schematic of the Stage 2 Model built using ArcGIS ModelBuilder.

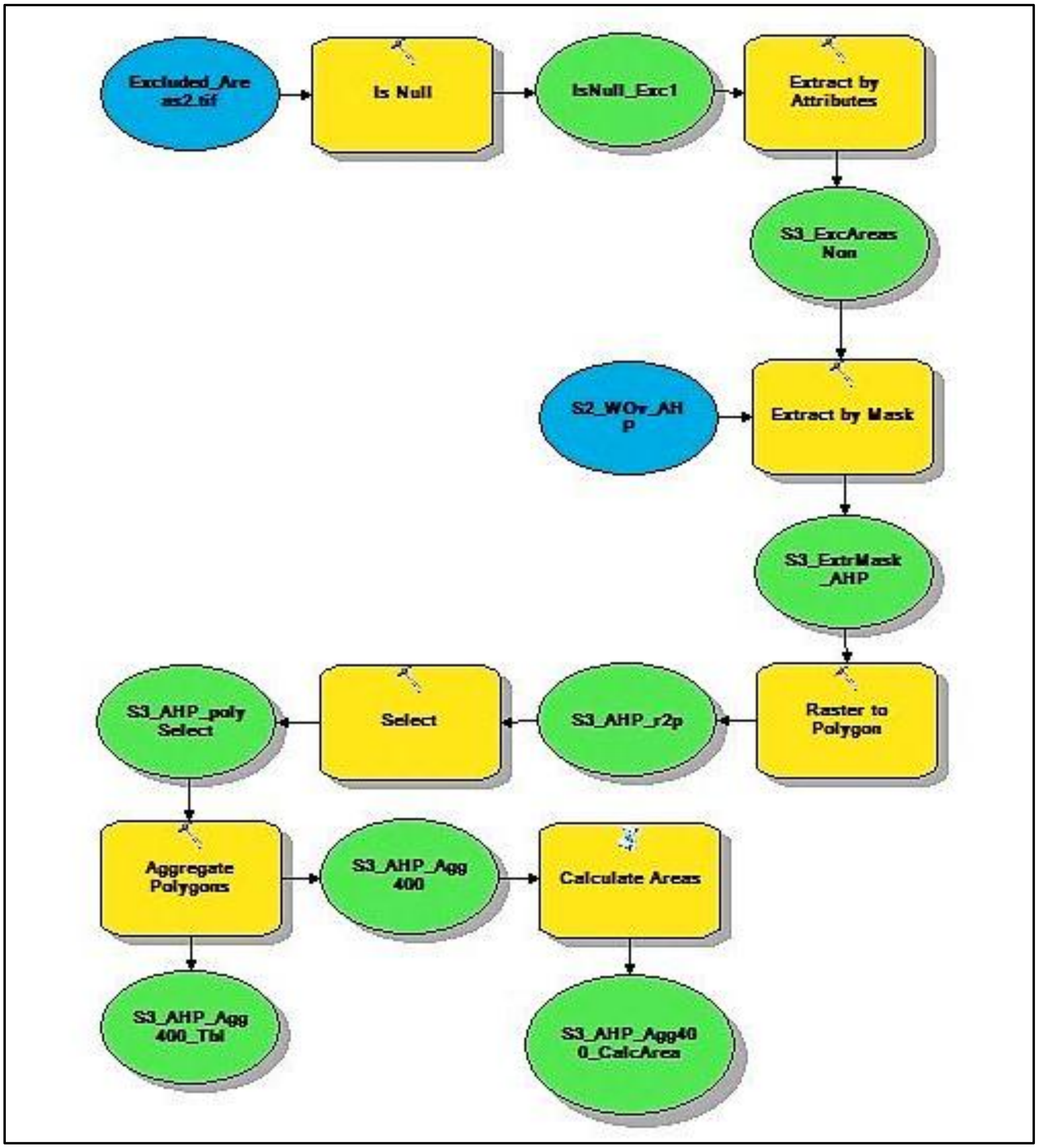

Figure 33: Schematic of the Stage 3 Model built using ArcGIS ModelBuilder.