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Modeling Seedbed Favorability Using a Biological Assay as an Indicator of Ecological Site Resilience

by

Alex R. Boehm

A thesis

submitted in partial fulfillment

of the requirements for the degree of

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To the Graduate Faculty:

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Acknowledgement

I am a runner. I like the long run especially but any will do. I don't run for the winning but mostly for the doing. I like the crowd around me, the other runners and spectators. I love the feeling of shared enthusiasm that got every runner there and the love and support from family and friends who are there to cheer you on. Each race is hard but I still do them. During hardest parts of every race I remind myself that I chose this path. I decided to step up to the starting line and I told myself I would finish. I remind myself of the other runners and the crowds around me who are cheering me on. So through pain and weakening will, I tell myself that can finish, even if it kills me.

For me finishing this thesis was a lot like running a marathon. I knew the course in front of me and I knew it would take a while to finish. Dr. Stuart Hardegree gave me the path and confidence I needed to finish. Dr Nancy Glenn showed me encouragement and leadership I needed to stay on the path. Dr Lejo Flores was critical for me to fully wrap the modeling together and to Dr. Kitty Lohse for her patience and understanding through the whole ordeal. I cannot underscore enough how grateful I am for their support throughout all of this process.

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I know that this was worth it, and it didn't kill me.

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Table of Contents

List of Figures

List of Tables

Modeling Seedling Germination Rate as an Indicator of Ecological Site Resilience

Thesis Abstract – Idaho State University (2015)

Rangeland vegetation in the Great Basin, U.S.A., is frequently disturbed by natural and human caused wildfire. Many areas have been converted to near-monocultures of introduced annual weeds such as cheatgrass (*Bromus tectorum*) and medusahead wildrye [*Taeniatherum caput*-medusae (L.) Nevski]. Resistance to disturbance and resilience of native and seeded-non-native plant communities follow topographic patterns associated with soils, slope, aspect and elevation. We hypothesize that the pattern of post-disturbance vegetation in these landscapes is correlated to topographic effects on seedbed temperature and water relationships. We further hypothesize that these microclimatic patterns across the landscape are consistent with NRCS Ecological Site Descriptions (ESDs), which integrate biotic and abiotic factors affecting current and potential vegetation distributions. This type of information can link microclimate to the landscape in a way that informs managers of potential species specific performance within an ESD. This study focuses on developing soil microclimatic indices and correlating them with both observed plant communities and potential vegetation states as described by site-specific ESDs and their associated State and Transition Models (STMs). We use long-term weather records from the region around Boise, Idaho, to estimate seedbed temperature and water relations using the Simultaneous Heat and Water (SHAW) model. Seedbed temperature and water potential is then used to drive hydrothermal germination response models to generate indices of seedbed favorability for plant establishment. The seedbed favorability, referred to here as a Rate Sum Index (RSI), represents a total number of potential progressions towards germination for a given grass species averaged over a monthly time step. In the first phase of the project we evaluate topographic effects on seedbed microclimate and develop methodology to distribute microclimatic and seedling establishment indices across example soils from the Boise Front Management Area (BFMA; 20,000 ha). In the second phase we conduct vegetation surveys and use remotely sensed vegetation data to determine whether the current distribution of ESDs is correlated to potential seedbed microclimate for target species. We used a stepwise regression approach to determine if the vegetation distribution was related to modeled RSI values within the watershed. The overall correlation was highest for perennial cover estimates but tended to be low (R^2 = .31), likely as a result of insufficient validation points for the cover estimates. Seedbed modeling and assessment of relative site favorability for perennial plant establishment can be useful in designing weather and microclimatic supplements for ESDs, and quantifying transition probabilities between alternative vegetation states. These tools support more effective restoration strategies for weed affected rangelands throughout the Intermountain region.

Chapter 1: Introduction and Background

Statement of Purpose

Ecological Site Descriptions (ESD) are a primary tool for assessing ecological health as they describe both current site status, and site potential for a healthy and fully functional state. ESD classification is primarily based on site-specific ground measurements of soil and vegetation status, knowledge of previous disturbance regimes, and understanding of the historical undisturbed site potential (Briske et. al., 2005; Mosely et. al., 2010; Morris and Monaco, 2012). Millions of hectares of Basin and Wyoming big Sagebrush (*Artemisia tridentata tridentata and Artemisia tridentata wyomingensis*) and bunchgrass communities in the western U.S. are currently in a degraded state due to the proliferation of introduced annual weeds and recurrent disturbance by wildfire. The resistance and resilience of these communities to annual weed invasion is climate dependent and increases at higher elevations that are cooler and receive more precipitation. Relative resistance and resilience at lower elevations is highly variable and appears to be correlated with local topographic and soil variability within the same general climatic regime. We hypothesize that this variability in resistance and resilience is due to local variability in soil microclimate as a function of slope, aspect and soil type. The purpose of this study is to quantify this microclimatic variability over space, and determine whether it can be correlated to existing plant community distribution and site resilience and resistance to weed invasion. Microclimatic characterization of this type could be used with ESDs to provide a more mechanistic description of ecological resistance, resilience and site potential. Microclimatic ESD supplements could also be generated at a larger spatial scale using Geographic Information System (GIS), modeling, and spatial weather, topography and soils information.

Background

Millions of acres of western rangelands are now dominated by non-native invasive plants such as cheatgrass (*Bromus tectorum* L.*)*, medusahead wildrye [*Taeniatherum caput-medusae* (L.) Nevski], (Young 1992; Young and Longland 1996; Davies 2008; Davies and Svejcar 2008). The expansion of these species has been in part a result of past management practices, land use patterns and global climate change (Mack 1986; D'Antonio and Vitousek 1992; Knapp 1996) and has resulted in significantly increased fire frequency and wildfire size (Pellant, 1996). The expansion of these weeds, due in part to the role they have in the fire cycle, have had negative impacts on ecosystem health, biodiversity, soil erosion, wildlife habitat and economic viability of rural communities (Sheley et al, 2006). Land managers seek conservation methods and strategies that mitigate and reduce the negative effect of weed expansion (Vasquez et al, 2010) but the most consistently used practice is seeding of perennial grass and shrub species in the year immediately after vegetation removal by wildfire (BLM 2007). A main constraint to rangeland plant establishment, however, is soil water availability for early plant establishment and subsequent plant survival (Call and Roundy 1991; Hardegree 2011; Hardegree et al. 2012a, b).

At a very broad scale, cheatgrass dominance and invasion trajectories have been linked to climatological factors that are related to site temperature and moisture variables (Bradley and Mustard 2006). At a more local scale, cheatgrass dominance is not uniform over the landscape, and in the Boise Front Management Area (BFMA) and other areas of the Great Basin, cheatgrass and perennial grass distributions are strongly dependent upon topographic and soil characteristics (Boise Foothills East Vegetation Management Environmental Assessment 2009; Reisner et al. 2013; Arkle et al. 2014). As cheatgrass is an annual plant, and most rangeland restoration management occurs in the year after wildfire, we hypothesize that site conditions for early plant establishment play a critical role in determining successful establishment and dominance of weedy species over seeded perennial grasses. Our strategy is to estimate topographic and soil effects on post-fire soil microclimate, to determine whether patterns of seedbed microclimate favor or disfavor annual weed species, and establish whether these patterns are correlated with post-fire disturbance patterns in the BFMA.

Our current understanding of ecosystem resistance and resilience to weed invasion suggests that ecological thresholds exist below which weedy species can dominate, and above which more desirable perennial species dominate (Chambers et al. 2014). Mapping of seedbed microclimate and correlation to existing patterns of post-disturbance vegetation would provide a mechanistic model in support of both resistance and resilience concepts, and quantitative information in support of the State and Transition Models that underlie current ESDs for Wyoming and Basin big sagebrush/bunchgrass plant communities in the northern Great Basin.

Ecological Site Descriptions, State and Transition Models, and Resistance and Resilience

Rangeland restoration is generally implemented within a framework that addresses the causes of succession and the ecological processes that are feasible for managers to apply (Sheley et al., 2006). These ecological processes are reflected in NRCS ESDs and STMs that are often used as a resource for restoration planning (Bestelmeyer et al., 2003). Structure, composition and dynamics of plant communities described in site specific ESDs and associated STMs provide managers with a conceptual map of potential vegetation change after certain types of disturbance (Briske et al., 2005). Generally these can be evaluated using three methods: trend analysis, rangeland health assessment, and development of similarity indices (USDA-NRCS, 2015a). Trend describes an ecosystem trajectory towards or away from a desired ecological state (Hernandez and Ramsey, 2013). Indicators of rangeland health are qualitative interpretations performed by rangeland specialists who use the results to infer both the relative integrity and stability of rangeland systems as well as potential degradation (Pyke et al., 2002). Similarity indices are used to compare an existing site to an undisturbed reference state described in an STM (Hernandez and Ramsey, 2013). By interpreting rangeland sites with these methods, managers can make informed decisions about rangeland restoration that account for the current status of a given site relative to a more desirable and resilient goal state, and the management changes necessary to transition to that state (USDA-NRCS, 2006; Chambers et al., 2014).

Restoration methods that result in ecological resilience to disturbance and resistance to invasive species are central to achieving stability in a post-restoration environment (Chambers et al. 2014). Chambers et al. (2014) described **resilient** ecosystems as being capable of regaining fundamental structure, processes, and function after system perturbation due to stress from drought, fire, over-grazing or other disturbance. Chambers et al. (2014) also described ecosystem **resistance** being related to how well a system can retain its structure, processes and functioning despite disturbance or invasion from alien species. Resistance to invasion by non-native plants has been linked to both abiotic and biotic factors driving important ecological processes (D'Antonio and Thomsen, 2004). These ecological processes are influenced by climate, weather, soils, topography and the floristic composition of a given plant community. Of those attributes, weather is the most highly variable over the relatively short term and can have an over-riding influence on initial restoration success (Hardegree et al., 2012b).

Climate is defined as the long term average of precipitation, solar radiation, wind speed, air temperature and humidity in a location or spatial domain (Hardegree, et al., 2012a). Weather describes the same variables but for a much shorter period. Weather is the principle driver of seedbed microclimate and has primary effects on early establishment processes of seed germination, emergence, and seedling growth and development (Hardegree et al, 2012b). Microclimatic patterns on the landscape reflect soil and plant community distributions and are correlated with a number of topographic variables such as slope, elevation and aspect (Jenny, 1941).

The Simultaneous Heat and Water (SHAW) model is a process-based model designed to estimate heat and water flux in the soil profile as a function of soil and surface properties, and surface weather inputs (Flerchinger, 2004). SHAW has been used in several previous studies to characterize seedbed microclimate and subsequent seedling establishment response of sagebrush-steppe vegetation (Hardegree et al. 2003, 2008, 2010, 2013; Flerchinger and Hardegree 2004; Flerchinger et al. 2012). SHAW model inputs require site specific data such as soil type, slope, aspect, elevation and weather (Flerchinger and Saxton 1989a,b). Weather is a critical driver of the model as it provides the temporal context for the simulation and is the source of the majority of microclimatic variability. Weather inputs for running the SHAW model include daily values for minimum and maximum air temperature, precipitation, solar radiation, dew-point and average wind speed (Flerchinger, 2000). Model output includes soil moisture and temperature at seeding depth that can be used to drive hydrothermal models of seed-germination response (Hardegree et al., 2013). The magnitude of predicted germination response can be used to estimate general microclimatic site favorability for early establishment. Species with high projected germination rates may be better suited to sites with short windows of seedbed favorability whereas species with lower rates may require more sustained levels of site favorability for establishment.

Linking microclimate processes to weather and climate can significantly aid in understanding the ecological processes that determine successful establishment of desirable plant species after wildfire (Hardegree et al. 2012a). Restoration planners can use historical weather records to retrospectively assess the probability of success or failure of a seeding project, and to better understand the restricted set of conditions necessary for successful plant establishment of desirable species (Hardegree et al., 2012a). A probabilistic description of the affects of climate on potential restoration success can then be used to design adaptive management strategies and contingency plans for longer-term restoration applications (Hardegree, 2012b).

Study Area

This study focuses on the 20,000 ha BFMA in the foothills north and east of Boise, Idaho. This area extends from the City of Boise to the first major ridge north of the city, and from Bogus Basin road on the west to Lucky Peak reservoir on the east. This area is primarily Bureau of Land Management (BLM) land (4300 ha) but also includes land owned by the City of Boise (770 ha), the State of Idaho (4700 ha), and various private land owners (7450 ha). This area has historically been used for grazing of sheep and cattle, but is currently primarily an open space recreational area for the City of Boise (Ada County, 2010). The eastern portion of this area is a designated Wildlife Management Area and a principal migration corridor for native ungulate species (Ada County, 2010). This area has burned multiple times in the last 150 years and is currently a patchwork of invasive annual weeds on more exposed southern slopes, and various native and non-native perennial plant communities on more protected northern slopes (Ada County, 2010). A major concern in this area is the potential for catastrophic runoff and erosion events as in 1959 when major flooding and soil movement occurred after a large wildfire and subsequent thunderstorm events. The most recent large scale fire in the area was in 1996 when 5700 ha burned just north of Boise, followed by flooding and debris flows (City of Boise, 2015). Multiple agencies spent $3.3 million focused on erosion and restoration of the burned area (City of Boise, 2015). As a result of large fires such as these, Boise City levied $10 million to fund land acquisition and invest in flood and erosion mitigation and rangeland restoration efforts in the year after the fire (City of Boise, 2015).

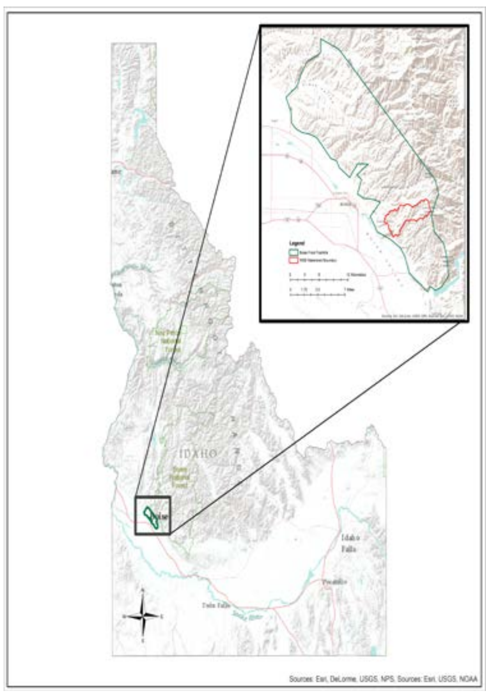


Figure 1: Boise Front Management Area with Warm Springs Basin Highlighted

Thesis Organization

This research is described in four chapters. The first chapter is the introductory material for the remaining thesis. The second chapter focuses on developing a conceptual model to characterize environment variability in soil microclimate in an idealized topographic scenario that explicitly evaluates the effect of slope, aspect and soil type on seedbed temperature and water availability. The potential effect of soil type and topographic position is evaluated using a bio-assay based on the predicted hydrothermal response of two native perennial grass species and cheatgrass. This bio-assay consists of calculated germination rate sums that provide a quantitative measure of seedbed microclimatic favorability for germination and early plant establishment (Hardegree et al., 2013). Chapter 3 develops methodology to expand the topographic analysis to assign soil and topographic archetypes for classifying microclimatic and favorability indices for the BFMA spatial domain. We also assess long-term local weather records and estimate hourly temperature and water potential at seeding depth for each soil/topographic category. The model results are assessed for spatial and temporal variability in seedbed microclimate and for relative response of cheatgrass and native grass species to topography and soil type. In Chapter 3, we also classify soil polygons in a sample basin of the BFMA based on microclimatic rate sum indices using the processes described in Chapter 2. We then use field data to classify current, post-disturbance plant communities with regard to annual and perennial plant-community composition. We use multi-temporal datasets derived from Landsat 8 Thematic Mapper (TM) imagery to map vegetation components and cover types for comparison with calculated rate-sum indices for individual soil polygons. We then use a random forests machine learning approach to assess the relationship between remotely sensed vegetation indices and hydrothermal indices for site favorability, and their relationship to currently mapped ESD distributions. Chapter 4 assesses the limitations and assumptions in this analysis and proposes additional analyses, and potential applications of this modeling technology for rangeland restoration planning.

Chapter 2: Topographic and Soil Effects on Seasonal Distribution of Hydrothermal Conditions for Germination

Abstract

In this study we used seed germination rate as an index for assessing relative favorability of seedbed microclimate for cheatgrass (*Bromus tectorum* L.*)*, bottlebrush squirreltail (*Elymus elymoides* [Raf] Swezey) and Idaho fescue (*Festuca idahoensis* Elmer) as a function of 25 topographic classes and four soil types (clay, sand, silt loam and loam). We first parameterized the SHAW model with topographic, soil and weather-input data to estimate soil temperature and water potential at seeding depth for a 30-year historical simulation. Hydrothermal germination rate models were then used to map relative favorability of seedbed microclimate as a function of soil type, topographic position, species and time of year. Model results indicated a stronger topographic effect on seedbed favorability for cheatgrass than for the two native grasses. Results also indicated relative topographic and soil gradient favorability that are consistent with observed distributions of annual weed and perennial bunchgrass species in the BFMA. These relationships can be used in conjunction with ESDs to identify topographic and soil conditions that may be relatively more or less resilient to weed disturbance after wildfire.

Introduction

Rangeland seeding guides typically acknowledge the importance of climate by listing species suitability for a given site as a function of mean annual precipitation (Jordan, 1981, Jensen et al., 2001; Ogle et al., 2008; Sheley et al., 2008). These recommendations, however, are based on the climatic requirements for adult plant communities. The range of microclimate conditions necessary for seedling germination and early plant establishment are much more narrow (Call and Roundy, 1991; Peters, 2000; Hardegree et al., 2003). Topographic and edaphic complexity also impact hydrothermal conditions across rangeland landscapes (Seyfried, 2000a) and this complexity contributes to the discontinuous distribution of invasive species such as cheatgrass in areas of complex terrain (Bradley, 2009). The patchy distribution of cheatgrass vs perennial plant communities is most likely a result of variability in available soil moisture as influenced by topography and soil texture (Geroy et al., 2011; Bullied et al., 2012; Moeslund et al., 2013; Smith et al., 2011). Topography, specifically slope and aspect, influence the relative amount of solar input a given site receives under conditions that may otherwise have identical weather inputs (Flerchinger and Saxton, 1989a), although different microclimatic conditions across the topographic landscape also impact soil development (Jenny 1941). Relationships between soil type and topography have been previously correlated with the distribution of annual weeds and perennial bunchgrass communities in the western United States (Reisner et al., 2013). Chambers et al. (2014) attributed ecosystem resilience and resistance to weed invasion to rangeland systems with higher water availability and associated higher productivity.

Lower elevation areas with higher temperatures and lower precipitation may still have local microclimatic conditions that favor resistance and resilience due to the ameliorating effects of areas of local topographic convergence such as northern exposures on solar radiation input to the soil (Bullied et al 2012).

Species and plant community distributions are highly correlated with average climate, but these relationships are primarily useful only at a very broad spatial scale (Shown et al. 1969; Shiflet 1994; Bradley and Mustard 2005; Vogel et al. 2005; Natural Resources Conservation Service 2006). Development of process-based models have helped significantly in understanding more local scale temporal and topographical variability in plant establishment rates (Hardegree et al. 2013; Bullied et al. 2012). A process for modeling near surface hydrothermal properties was outlined by Hardegree et al. (2003) using the SHAW model to provide input for estimating hydrothermal germination response. Bullied et al. (2012) also used the SHAW model to investigate germination and establishment response of crop species as a function of topographic position on the landscape. Hardegree et al. (2013) suggested that germination rate sums could provide a quantitative bio-assay of general seedbed favorability for early plant establishment, but only evaluated temporal variability in seedbed microclimate. Hardegree et al., (2013) focused on assessing temporal variability in seedbed microclimate and germination response on only one soil type with no topographic considerations. In this study we extend the application of germination rate sums to quantify topographic variability in seedbed favorability as a potential index of site conditions that favor or disfavor dominance by annual weeds.

The purpose of this study is to use a seedbed microclimatic model to assess topographic and soil variability in temperature and water potential as they might affect early establishment of perennial and invasive annual grass species. We use the SHAW model which simulates soil temperature and water potential as a function of depth, soil and surface properties, as affected by the time-series of meteorological inputs (Flerchinger, 2012). The SHAW model has been used extensively to characterize soil microclimate for multiple agricultural and natural resource applications including the interpretation of seedling establishment success in arid-land systems (Hardegree et al. 2004, 2008, 2010, 2013) and to derive topographic effects on plant establishment in agricultural systems (Bullied et al. 2012). Along with topographic and soil texture data inputs for SHAW include precipitation, air temperature, humidity and wind speed (Figure 2). Soil microclimatic conditions are compared using a bio-assay based on hydrothermal germination response as described by Hardegree et al. (2013). Cheatgrass has been previously shown to germinate approximately twice as fast as the most rapidly germinating native perennial species (Hardegree et al. 2013). The bottlebrush squirreltail accession used in this study represents the more rapidly germinating perennial species and Idaho fescue the more slowly germinating species evaluated previously by Hardegree et al. (2013). Four common soil types from the BFMA are evaluated for 25 topographic categories of slope and aspect relative to potential germination response of the two native perennial bunchgrasses and cheatgrass. In this study, we use germination rate sums (Hardegree et al. 2013) as an index for assessing relative species performance as a function of topography and soil type for a 30 year weather record for the Boise location.

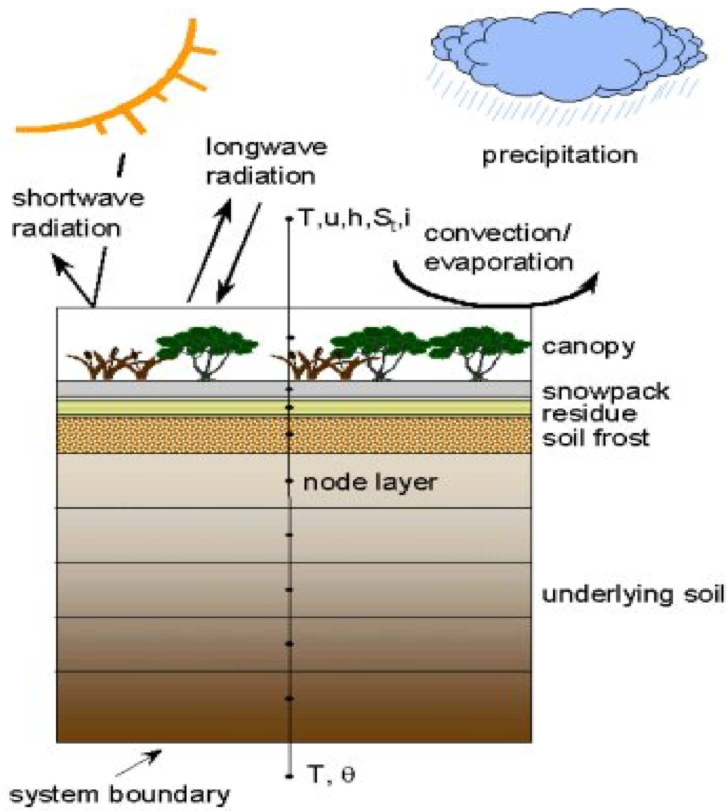


Figure 2: Generalized Weather Interaction With The Landscape (Flerchinger, 2000). Output: T = Temperature, Θ = Water Content. Input: T = Temperature, u = wind, h = Humidity, S_t = Solar Radiation, i = Precipitation.

Methods

The general methodology for the microclimatic simulation and estimation of germination rate sums is based on the procedure described by Hardegree et al. (2013) and Flerchinger and Hardegree (2004). Modifications for this study include 4 soil types common to the BFMA, 8 aspect categories (in 45 degree increments) and 4 slope categories (0, 15, 30, 45%). SHAW requires a number of parameter files to run including the initial conditions of soil temperature and moisture as a function of depth, daily or hourly weather inputs including air temperature, precipitation, wind speed, relative humidity or dew point, and solar radiation (Flerchinger and Saxton 1989a,b). SHAW also requires knowledge of physical site characteristics including soil texture and bulk density, slope, aspect, and latitude (Flerchinger and Cooley, 2000). Site effects on favorability for early plant establishment is determined by estimating hydrothermal germination response and calculating site-specific germination rate sums using the statistical-gridding hydrothermal model described by Hardegree et al. (2013). The specific species used to assess site favorability in this study are Idaho fescue, bottlebrush squirreltail and cheatgrass.

We performed separate microclimatic simulations for each hydrologic year (October 1st to September 30th) of the 30 year study period. Each simulation was initialized with primarily dry conditions starting on July 15th preceding the start of a given hydrologic year. The initial starting date for each year was used to reduce variability caused by unknown initial soil conditions at the beginning of each annual simulation (Hardegree et al., 2013). Topographic simulations were based on weather records for the Boise Airport (43.5613 N, -116.2182 W) with an approximate elevation of 900m. Average precipitation for this site is around 300 mm per year with annual temperature ranges of 17.2 to 4.3 C (WRCC, 2015). Soil types were based on four common soils located in the BFMA (Table 1). Twenty-five slope and aspect categories were used to evaluate topographic effects on seedbed microclimate. Slope categories were 0, 15, 30 and 45% which span the range of typical slopes in the BFMA. Aspects were divided into 8 categories in 45 degree increments from north (0, 45, 90, 135, 180, 225, 270, 315), yielding 100 unique topographic and soil-type categories (Table 1 and Figure 4). Assumptions that were made were based on a generalized approach to the model. Since soil depth is highly variable and difficult to estimate surface textural profiles were assumed to be homogeneous with depth.

Soil	Bulk Density g/cm^3	% Sand	% Silt	% Clay	Slope: 4 classes in percent	Aspect: 8 Classes in degrees
Clay	1.74	22	32	46	0, 15, 30, 45	0,45,90, 135, 180, 225, 270, 315
Loam	1.18	35	45	20	0, 15, 30, 45	0,45,90, 135, 180, 225, 270, 315
Silt Loam	1.51	26	55	19	0, 15, 30, 45	0,45,90, 135, 180, 225, 270, 315
Sand	1.31	88	10	2	0, 15, 30, 45	0,45,90, 135, 180, 225, 270, 315

Table 1: Soil bulk density, texture and topographic categories used for analysis.

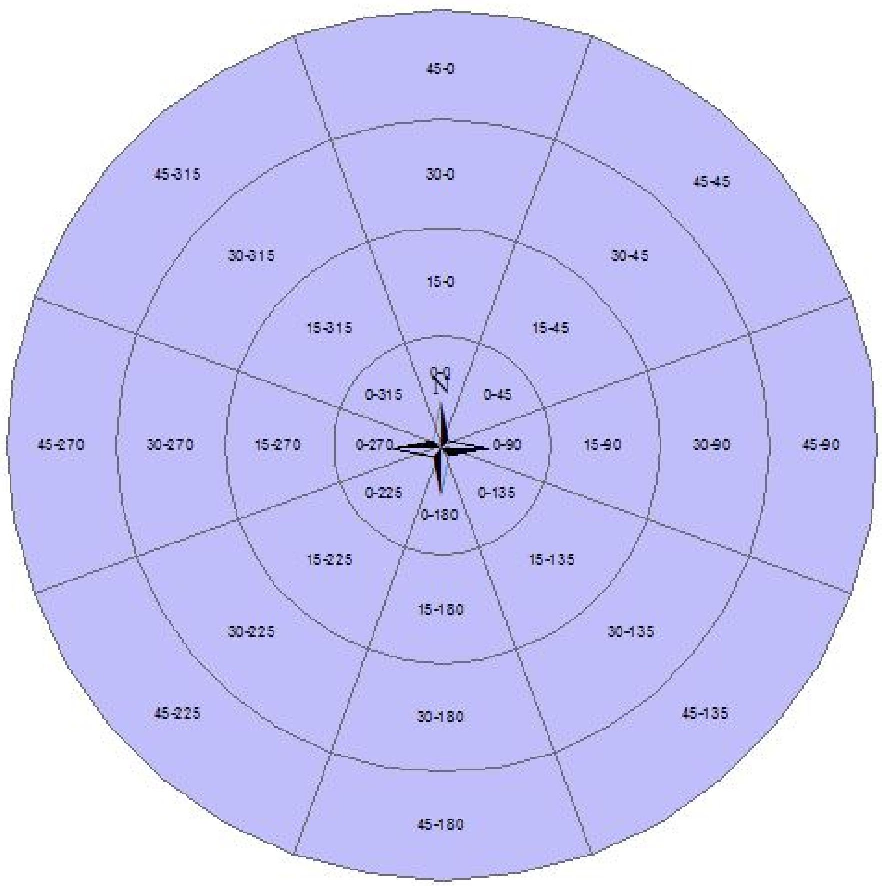


Figure 3: Spatial Pattern Used To Map Model Output Distribution. Numbers represent Slope and Aspect. Flat slopes are in the center and steeper slopes are on the outer ring.

Hydrothermal Germination Model

The SHAW modeling procedure yielded soil temperature (EC) and water potential (MPa) estimates at seeding depth (2 cm) for every topographic and soil category for every hour of the 30-year simulation. Hourly SHAW estimates of soil temperature and water potential were used as input to drive the hydrothermal germination response models described by Hardegree et al. (2013) for the three test species. These hydrothermal germination models apply a statistical-gridding procedure to estimate germination rate of all of the seeds in the population as a function of water potential and temperature conditions during a given hour of the simulation (Hardegree et al. 2013, 2015). We selected the 25th percentile of seeds as representative of the most vigorous seeds within a given population. We estimated hourly germination rate for each hour of the simulation for the 25% seed subpopulation, and also estimated aggregated germination rates at the daily, monthly, seasonal (winter, spring) and annual (hydrologic year) time step (Hardegree et al. 2013). Aggregated rate sums of this type represent the overall seedbed favorability during a given time period and provide a quantitative index for comparison of years, seedlots, and relative germination response as a function of slope, aspect and soil type (Hardegree et al., 2013).

Rate Sum Index and Interpretation

Germination rate (25%) was estimated for each species and for each hour of the simulation for every topographic and soil category. Hourly germination rates represent the fractional progress per hour towards germination for the specified subpopulation (Biedenbender and Roundy 1996; Hardegree and Van Vactor 2000). The Rate Sum Index (RSI) is the cumulative aggregate rate summation over a particular time period and also represents the estimated germination progress of a given subpopulation over a specified time period. An RSI score of 1 represents full germination of a given subpopulation. The RSI value also represents the number of times a given subpopulation would be expected to germinate if the identical subpopulation were replanted immediately after seeds from the previous planting germinated. RSI is, therefore, a bio-assay of relative site favorability for a given location and time period. For example if a characterized topographic condition had an RSI of 1 then that microclimate was sufficiently favorable for that specified subpopulation to germinate once. Subsequently a rate sum of 2 or 3 would indicate there would be 2 or 3 opportunities to germinate in that time frame. Conversely if a given site never achieves a rate sum of 1 than the RSI would indicate insufficient favorability for that species to germinate during that period of time. The RSI only reflects a probable favorability or lack thereof for a given species based on temperature and water potential and does not account for other factors that influence germination (Hardegree et al., 2013).

Analysis of the Model

Given the complexity of the model and potential range of outputs, a generalized regression approach was used to identify RSI patterns as a function of topographic and soil variability. We focus on differences in model estimates of RSI as distributed throughout an averaged year and across individual months, topographic units, soil types, and species. We evaluated differences in RSI as a function of 25 slope and aspect categories, four soil types and the three species. A Generalized Linear Mixed Effects ANOVA was used to evaluate main factor effects and a Tukey's Studentized Range Test was used to evaluate significant differences among factors. Since we are investigating general patterns of species' response we focus on the 25% subpopulation of each seed lot in these analyses. To address the temporal context, we classified seasonal effects by dividing each year into 3-month periods and for purposes of this analysis' defined winter as December, January, and February; spring as March, April, and May; summer as June, July and August, and fall as September, October and November. The distribution of rate sums throughout the year was predicted for each topographic category and each soil type. The general work flow for modeling and analysis is represented in Figure 4.

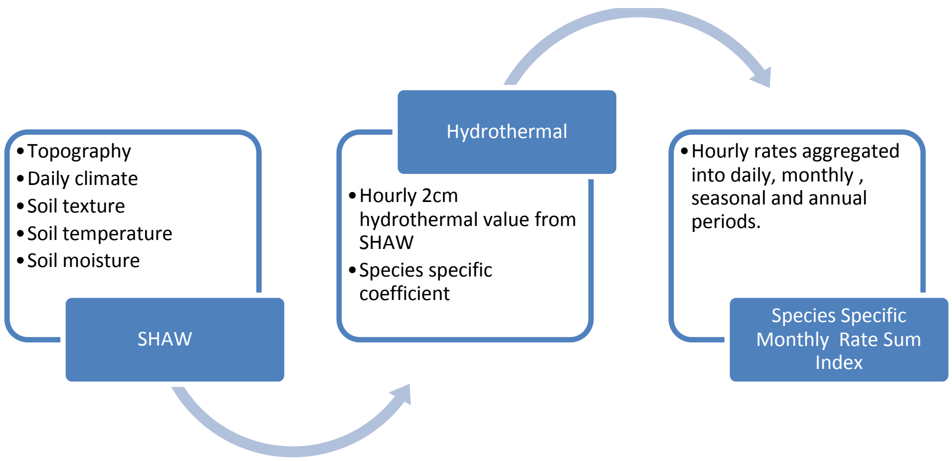


Figure 4: General flow of combined SHAW and Hydrothermal Germination Model (SHMODEL)

Results

There were four class variables used in the ANOVA; the 4 soil types, the 3 species, 25 topographic categories and 12 months over 31.145 years of climate data. Total number of RSI observations was 112,122. The adjusted R^2 was 0.61 with a RMSE of 0 .13. The degree of freedom was 95%, and each class was significantly different from each other. The Tukey's Honest Significance Difference (HSD) test was used to identify the significance of individual class similarities and differences.

Soils

Inter-soil comparisons indicated significant differences between clay and sand but not between loam and silt-loam (Table 3). Figure 5 shows RSI values for each month to reflect overall average annual patterns throughout the 31 year simulation. The highest rate sums occurred in the spring with the fall period providing the next highest period of germination favorability (Figure 5). Of the four soils clay had the highest RSI value for every month (Figure 5). The loam had the second highest RSI values in the spring and had equal to slightly better RSI than silt loam in the fall. Sand provided higher RSI values than both loam and silt loam in the fall but gradually fell below loam and silt-loam in the spring.

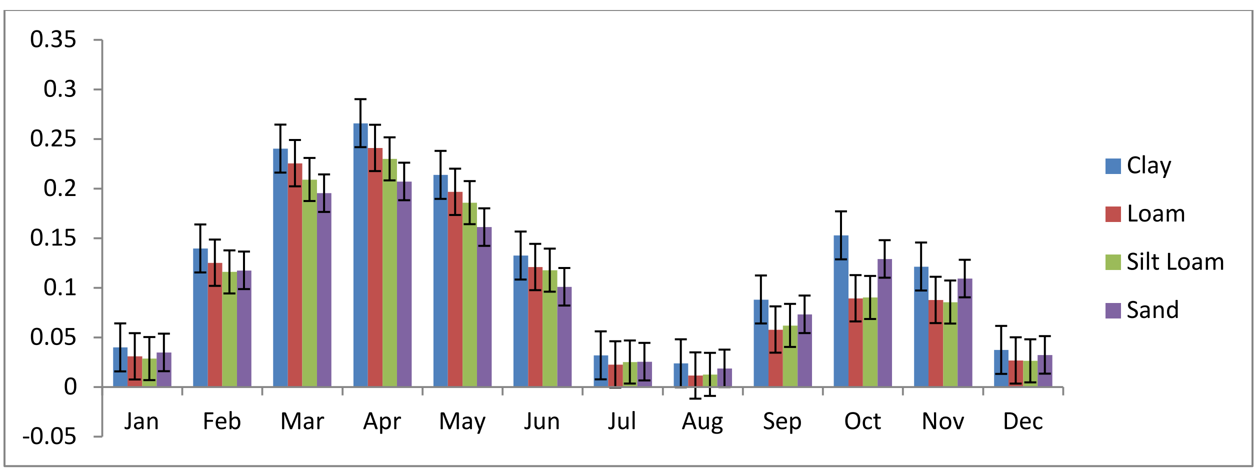


Figure 5: Average Monthly RSI Values Of All Species By Soil Type With Standardized Error Bars. Winter = December to February, Spring = March to May, Summer = June to August, Fall = September to November.

Tukey's Studentized Range HSD Test For Soils	
Alpha	0.05

Error Degrees of Freedom		108522		
Error Mean Square		0.015855		
Critical Value of Studentized Range		3.6332		
Comparisons significant at the 0.05 level are indicated by ***				
Soil Comparison	Difference Between Means	Simultaneous 95% Confidence Limits Upper and Lower		
clay-sand	0.029769	0.027028	0.03251	***
clay-silt-loam	0.036467	0.033743	0.039192	***
clay-loam	0.037255	0.03453	0.039979	***
sand-clay	-0.029769	-0.03251	-0.02703	***
sand-silt-loam	0.006699	0.003958	0.00944	***
sand-loam	0.007486	0.004745	0.010227	***
silt-loam-clay	-0.036467	-0.039192	-0.03374	***
silt-loam-sand	-0.006699	-0.00944	-0.00396	***
silt-loam-loam	0.000787	-0.001937	0.003512	
loam-clay	-0.037255	-0.039979	-0.03453	***
loam-sand	-0.007486	-0.010227	-0.00475	***
loam-silt-loam	-0.000787	-0.003512	0.001937	

Table 2: Differences in Soil Types as modeled by Tukey's Studentized Test

Species

RSI values for each species were relatively consistent between soil types and temporal periods. The Tukey's Studentized Range Test indicated no significant difference (F = 0.0022) between the three species tested (Appendix A, Table 4). In Figure 7 each species is being used to represent patterns of peak germination for all soils throughout seasonal units. Cheatgrass had higher rates than both squirreltail and Idaho fescue. Idaho fescue had the lowest rates of all the species. The spring period was consistently more optimal for each species with fall having the second highest rates (Figure 7). Both winter and summer had relatively low rates compared to the other seasons.

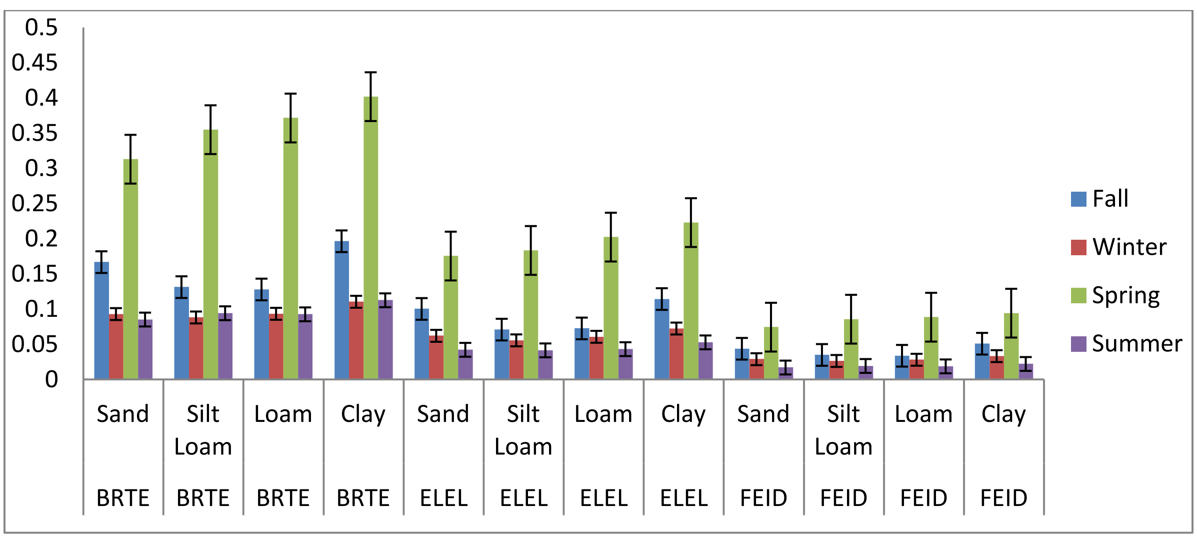


Figure 6: Overall Specie Performance By Soil And Season.

Temporal Patterns

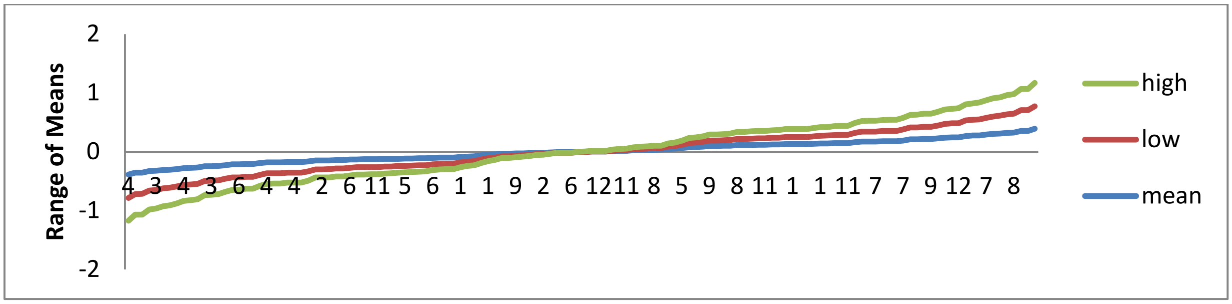


Figure 7: Range Of Monthly Mean Differences Of RSI Values. Months Are Represented Numerically For A Calendar Year on the X-Axis.

Temporal differences varied by month with some periods having similar RSI values to others. June typically had similar rates to October and November and December and January were similar to each other as a result of each species having lower germination rates. Trends for these periods differed however for the spring and fall periods with October and April being the most different from each other (Figure 7).

Topographic Patterns

Spatial patterns of species distribution varied the most for cheatgrass and less so for the two perennial grasses (Figure 8). Figures 8 and 9 are representing Silt loam, which is being used to represent the four soils. Figures 8, 10, 12, and 14 reflect the fall and spring topographical distributions of RSI from a top down view. Figures 9, 11, 13, and 15 are representing RSI values for Fall and winter as they trend up and down slopes. Fall RSI values were typically higher in south west facing aspects while switching to having higher rates occurring mostly in the north east aspects in the spring (Figures 8, 10, 12, 14). Cheatgrass rates were typically twice as high as squirreltail and three times as high as Idaho fescue (Figure 6). Cheatgrass RSI values were highest on clay soils and lowest on sandy soils (Figure 6). Cheatgrass also had the highest variability for all soil types along topographic categories (Table 3 and Figure 8). Squirreltail and Idaho fescue had lower variability than cheatgrass among all topographic categories (Figure 6). In the spring period all three species had higher rates across topographic categories in clay, loam and silt loam and less so in the sand (Figures 9, 11, 13, 15). In the fall period sand outperformed silt-loam and loam particularly in the south facing aspects (Figure 8). Squirreltail and Idaho fescue were less responsive to topography in the spring when soil moisture and temperature are less prone to rapid fluctuation in temperature and moisture (Figures 9, 11, 13, 15). Idaho fescue was less responsive overall to topography and favored southwest clay soils in the fall only slightly more than the other soils. Overall, the variance in topographic effects for the perennial species was less important than it was for cheatgrass which had a stronger response to topography in all soils (Figures 9, 11, 13, 15).

Figure 8: Example Of Topographic Patterns For RSI Values of all 3 Species In Silt Loam. FEID = Idaho Fescue, ELEL = Squirrel Tail, BRTE = Cheatgrass. From center of the rings Slopes range from 0, 15, 30 and 45%

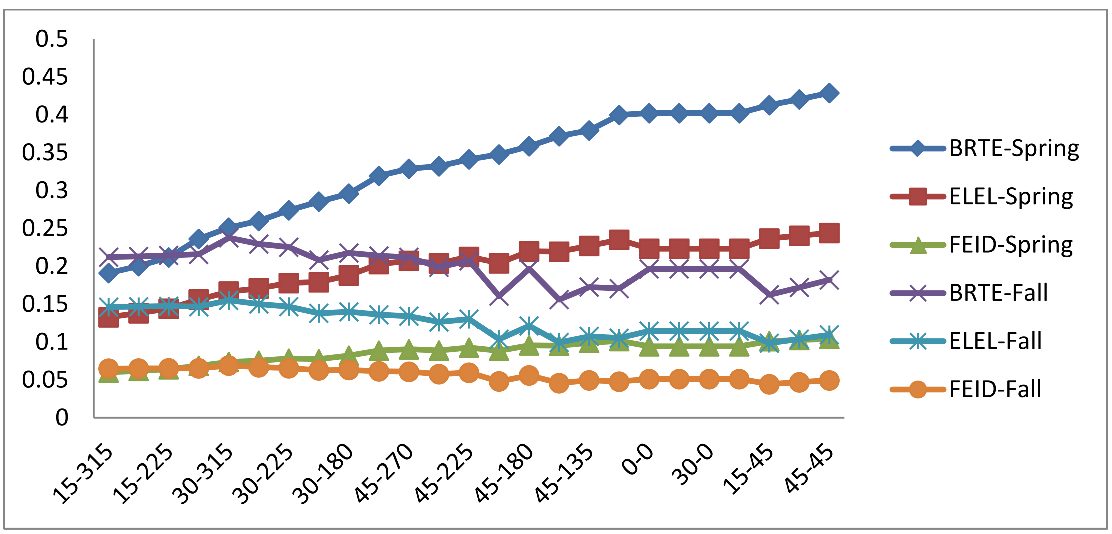


Figure 9: Comparison Of Rate Sum Index (RSI) Between Spring And Fall Periods In Clay Soil. X-Axis Indicates Slope – Aspect Categories, I.E. 15% Slope – 315 Degree Aspect.

Figure 8 and 9 provide examples of the topographical distribution observed for RSI across the 25 categories used in the study. All soils responded similarly and in proportion to their soil type as observed in Figures 5 and 6. Spring and fall were plotted against each other and tended to be the more important seasons for RSI over winter and summer. Spring RSI had higher rates toward the northeast aspects along increasing slope angles (Figures 7, 9, 11, 13). The opposite pattern occurred during the fall when rates were lower but tended to be higher in southwest slopes (Figures 9, 11, 13, 15). Cheatgrass had the most distinctive response to topography with the highest variance relative to topography for all soil types. Squirreltail also responded more significantly than Idaho Fescue to topography but with proportionate RSI values. Idaho fescue had the lowest response to topography relative to both cheatgrass and squirreltail.

Discussion

The use of climate information in rangeland restoration planning has been primarily applied to the process of site-appropriate species selection. Annual precipitation values generally guide managers in determining appropriate plant materials for a given location (Jensen et al., 2001; Ogle et al., 2008). The timing of planting is also generally selected to occur prior to the principal season of precipitation with fall being the most common planting period in the Great Basin (Roundy and Call, 1988). Planting in the fall is primarily done for logistical reasons, but allows the seeds to take advantage of all potentially favorable periods of growth and establishment in the subsequent winter and spring (Monson and Stevens, 2004).

Improving seedbed microclimate is the primary rationale for most site preparation treatments used in rangeland seeding (Hardegree et al., 2011). Planting treatments are focused on optimizing seedbed temperature and moisture conditions and providing safe sites for germination and establishment (Call and Roundy, 1991; Krueger-Mangold et al. 2006). Seeding strategies also emphasize reducing resource competition with undesirable weed species that would otherwise inhibit successful establishment (Sheley et al. 2006). Managers selecting among alternative site preparation and planting treatments, however, do not generally consider microclimate differences as a function of slope and aspect, although they do make decisions based on equipment access in areas of complex terrain. Individual seedbed treatment effectiveness may not be as significant in periods when moisture is generally available, or conversely when climate conditions are so poor that all treatments are ineffective (Wood et al. 1982; Eckert et al. 1986; Roundy et al. 1992).

This study highlights the spatial and temporal variability in seedbed microclimate and site favorability for plant establishment as a function of soil type, topography, and species. Hardegree et al. (2013) also demonstrated high variability in precipitation among both individual seasons and years for similar field sites near the BFMA location. These data highlight the extreme spatial and temporal complexity in these systems and the degree to which generic management prescriptions may ignore important microclimatic differences over space and time. Whereas Hardegree et al. (2013) highlighted impacts of weather variability, this study extends that point by considering topography and soil type. By considering topographic effects on seedbed microclimate we can potentially quantify site characteristics that yield resistant and resilient plant communities and account for high local variability in plant community structure and restoration success in areas of complex terrain.

Soil texture has a significant impact on germination rate and site favorability, but this impact varies throughout the year (Figure 6). All soil performed similarly relative to each other among topographic categories in terms of general seasonal pattern and seedlot response. Clay soil provided better site favorability in general throughout the year. Sandy-soil site favorability was more variable among different seasons than the other soils tested. Sand favorability was relatively higher than for the loam and silt loam soils in the fall but relatively lower in the spring. Though sand had relatively high seasonal RSI values in the fall, it generally generated lower cumulative RSI values overall when compared to the other soil types. Loam and silt loam soil types performed similarly to clay throughout the year with higher rates in the spring and fall. Coarse soils have a higher rate of thermal conductivity than fine grain soils, along with higher matric potential during wet periods (Abu-Hamdeh and Reeder, 2000). Species such as cheatgrass with high germination rates are likely better suited to taking advantage of these conditions during favorable periods of soil water availability.

Cheatgrass also exhibited higher RSI values in soils and topographic areas where it is not typically observed to dominate in the field (Zouhar, 2003; Reisner et al., 2013). This indicates that despite a high germination rate potential in north and north east aspects in the spring, there are other factors contributing to their observed lack of dominance in these topographic categories. Regardless, cheatgrass seems to dominate in the most stressful topographic locations. This may partially result from its ability to germinate rapidly in what are relatively short windows of opportunity on southern exposures, and by having relatively large seed numbers that can absorb the higher mortality rates in these areas. Squirreltail and Idaho fescue produced much lower relative RSI values in sandy soils that tend to also dominate on southern exposures.

In the BFMA as in other study areas, cheatgrass tends to dominate in south and south west aspects and on sandy soils (Zouhar, 2003; Reisner et al., 2013). Higher germination rates in Clay and Loam soils may also be more favorable microclimates for subsequent growth and development, and yield more resilient and resistant plant communities in general. This pattern is similar to trends proposed for higher elevation and higher precipitation sites (Chambers et al., 2013). This study presents idealized categories of topography and soils that may not realistically describe actual topographic and soil distributions across the landscape. For example the soil texture and depths are assumed to be consistent for each topographic category. Practical application of these results must take into account the actual distribution of soil types and slope and aspect categories in the BFMA. In this study, RSI values were highest in north east aspects, but only a small percentage of the areas in the BFMA are in this topographic category. The majority (67%) of the topographic categories in the BFMA occur on southern aspects within the study domain with aspects between 135 and 270 degrees (Figure 17). Northern aspects with higher RSI values occur on only a third of the region of interest. Cheatgrass had a higher sensitivity to topography than either squirreltail or Idaho fescue, therefore, germination rates for cheatgrass in these soils likely peak in the fall rather than the spring due to the predominance of southern aspects. Squirreltail and Idaho fescue might respond similarly but are more likely to germinate over a longer period and be less dependent upon topography and more so on soil type.

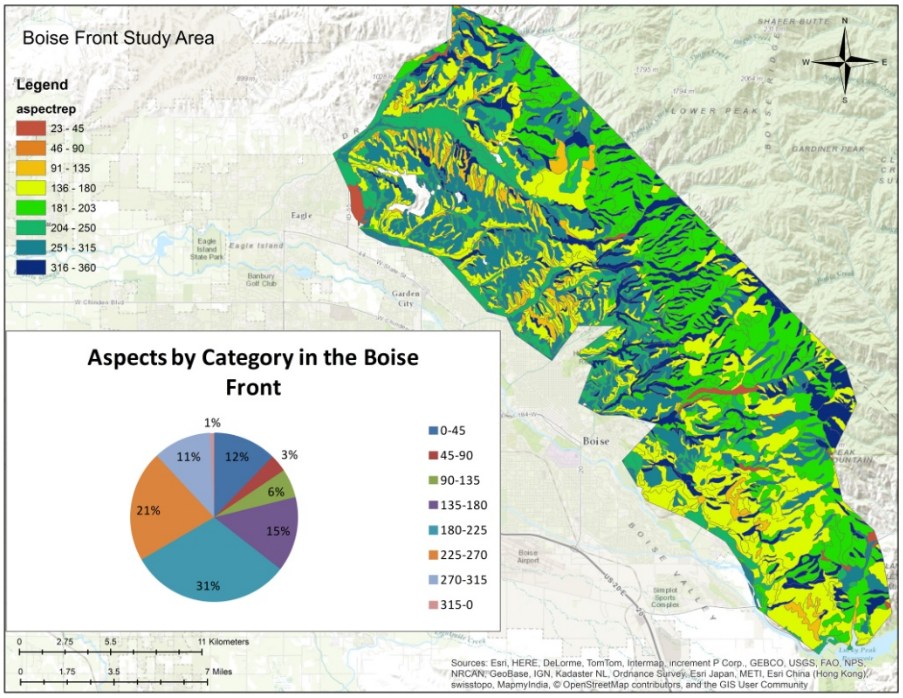


Figure 16: Aspect Distribution in the Boise Front Management Area.

It should be noted that our model simulations ignore a number of biotic and abiotic factors that might also affect germination and emergence in the field (Egli and TeKrony, 1996; Beckstead et al., 2007). We believe, however, that the simplified field status of post-fire seedbeds in this region are very similar to the type of conditions simulated in this study and that our simulations capture the major influences of seedbed temperature and moisture on seed germination, early establishment and growth. The hydrothermal models for each species have been extensively tested in lab studies that simulate the range of potential thermal conditions that effect cumulative germination response in the field (Hardegree et al., 1999; Hardegree, 2006a,c). It is more difficult, however, to simulate variable-water potential effects in the laboratory that adequately reflect field conditions (Hardegree, 2013). Progress toward germination has been shown to largely occur during favorable periods of low water stress and moderately suboptimal temperatures (Hardegree, 2003). Roundy et al. (2007) and Rawlins et al. (2012) have used this observation to simplify the hydrothermal modeling approach and were able to obtain reasonable predictions for field germination responses considering only thermal response above a threshold value of water availability. Roundy et al. (2007), James et al. (2011) and Boyd et al. (2013) noted that relatively complete germination generally occurs in most years for non-dormant species, and that the principle bottleneck for seedling establishment is post-germination mortality before emergence. We believe that these studies validate the relationship between seedbed microclimate and germination response, however, and that predicted germination response and RSI values provide a valuable bioassay for characterizing the general favorability of seedbed microclimate for both germination and subsequent growth and establishment of rangeland plant species. Separate analyses should be pursued, however, to identify the distribution of episodic periods of potential mortality from post-germination freezing and drought (James et al., 2011; Boyd and Lemos, 2013).

Model results indicated a stronger topographic effect on seedbed favorability for cheatgrass than for the two native grasses. The relative topographic and soil gradients favorability are consistent with observed distributions of annual weed and perennial bunchgrass species in the BFMA. These relationships can be used in conjunction with ESDs to identify topographic and soil conditions that may be relatively more or less resilient to weed disturbance after wildfire. ESDs for soils in the BFMA could include RSI as supplemental information for quantifying the level of management required to facilitate restoration after a fire. A loamy or clay soil with a high RSI value for multiple species would indicate a higher probability for seeding success. Whereas low RSI values for south facing sandy soils would indicate that state transitions between undesirable and desirable plant communities would be more difficult and seasonally dependant.

Conclusion

This modeling approach provides a method for understanding the distribution of seedbed favorability for plant growth and establishment in complex terrain. We believe that these tools may provide a quantitative description of topographic effects that are similar to elevational and associated precipitation differences that have been shown to be correlated with ecological resilience and resistance to annual weed dominance (Chambers et al., 2013). Precipitation variability is a primary driver for seedbed microclimate but characterization of precipitation alone does not describe the variability in plant community distribution generally seen in areas of complex terrain. In this study, we used a hydrothermal based rate sum index as a quantitative value for assessing the relative distribution of favorable seedbed microclimate as a function of soil type, slope and aspect. Rate sum values can be used to understand potential species performance in complex terrain, but also inform us about topographic patterns of potential resilience and resistance to weed invasion. RSI indices can also be used to quantitatively evaluate historical establishment success and failure, and potential climate change effects on seedbed microclimate and potential restoration. As a quantitative index, species-specific rate sums may also provide a feasible means to determine potential pathways between ecological states, and to inform economic assessments of alternative restoration strategies.

Chapter 3: Application of RSI Model as an Assessment Tool for Resistance and Resilience

Abstract

We evaluated the relationship between the Rate Sum site favorability Index and vegetation state in the Boise Front Management Area as an index of site resilience and resistance to invasive weeds. We used remotely sensed vegetation data and ground surveys to determine whether the current distribution of Ecological Site Descriptions is correlated to potential seedbed microclimates for perennial and annual plant species as a function of topography, elevation and soil type. We used a stepwise regression approach to determine if the vegetation distribution was related to modeled Rate Sum Index values within the watershed. The overall correlation was highest for perennial cover estimates but tended to be low (R^2 = .31) likely as a result of insufficient validation points for the vegetation cover estimates. Seedbed modeling and assessment of relative site favorability for perennial plant establishment can be useful in designing weather and microclimatic supplements for ESDs, and quantifying transition probabilities between alternative vegetation states. These tools will support more effective restoration strategies for weed affected rangelands throughout the Intermountain region.

Introduction

Ecological Site Descriptions (ESDs) and related State and Transition Models (STMs) are primary references for restoration management planning in the western United States (USDA-NRCS, 2015a; Westoby et al., 1989). ESDs provide information about the structure, composition, and dynamics of plant communities within mapping units consisting of a homogeneous soil type (Moseley et al., 2010). ESDs represent distinctive land types with specific physical and biotic characteristics that differ from other kinds of land and that respond in their own distinct manner to natural or artificial disturbance (Bestelmeyer and Brown, 2010). Corresponding State and Transition Models associated with a given ESD provide alternative vegetation scenarios that might occur at a given site based on disturbance history and/or management (Briske et al., 2005).

Ecological Site Descriptions provide critical information on the ecological processes underlying potential restoration strategies but landscape disturbances such as wildfire generally occur at multiple orders of magnitude greater scale than is typically described by a soil polygon or ESD boundary (USDA-NRCS, 2015b; Westoby et al., 1989). Remote sensing and the ability to classify ecological processes across the landscape are essential for development of cost effective rangeland restoration applications at the management scale (Willis, 2014; Hernandez and Ramsey, 2013). Remote sensing of ecological indicators is relatively non-invasive, provides quantitative data, and is applicable over a large range of spatial and temporal scales (Wiens et al., 2009; Crabtree et al., 2009; Cook and Hockings, 2011).

Remote sensing has been used previously to estimate the current vegetation state within a given ESD (Ramsey and Hernandez, 2013). Ramsey and Hernandez (2013) also used a remotely sensed Soil Adjusted Vegetation Index (SAVI) as a way to perform trend analysis and to assess alternative state conditions among similar ESD boundary locations. Remote sensing has also been used in numerous studies to validate and improve environmental models (Maas, 1988; Knight et al., 2006). Typically these approaches use various environmental indices and ground validation data to classify plant and soil conditions within a given area and compare the results to predictive model data (Maas, 1988). Mitchell et al. (2015) combined multiple spectral indices derived from hyperspectral satellite observations and ground validation to yield estimates of ground cover using a machine learning methodology referred to as random forests (Breiman, 2001). Random forests analyses have proven useful in other studies for determining optimal indices for comparison of alternative ecological models (Ramsey and Hernandez, 2013; Immitzer et al., 2012; Mellor et al., 2013).

Existing ecological states can transition to other states either through naturally occurring successional processes, or more rapidly after disturbance (Briske et al., 2005). Trend analysis of alternative ecological states (Ramsey and Hernandez, 2013) can also provide information about relative ecological resilience and resistance to weed invasion in a given location (Chambers et al, 2014). Chambers et al. (2014) defined ecological resilience relative to the amount of time it would take for an ecosystem to return to an initial condition after disturbance. Chambers et al. (2014) indicated that in cold desert shrub plant communities, increased elevation and precipitation along with decreasing soil temperatures are correlated with improved ecosystem resilience and resistance to invasion by introduced annual grasses such as cheatgrass. We propose that generalized soil temperature and precipitation gradients oversimplify spatial patterns of soil temperature and moisture and that microclimatic modeling at a finer spatial scale could be used to account for topographic and soil variability as it might affect ecological resilience and resistance.

Successful restoration after wildfire disturbance is dependent on favorable soil temperature and water availability in the seedbed during critical periods of plant establishment (Hardegree et al., 2003). Seedbed microclimate is affected by local weather and elevation gradients of precipitation and temperature, but also by topographic position on the landscape and soil type (Thornton et al., 1997; Bullied et al., 2012; Hardegree et al., 2012). Reisner et al. (2013) indicated that there are soil, topographic and climatic conditions that favor annual grass dominance and Chambers et al. (2014) linked general landscape gradients of precipitation and temperature to ecosystem resilience and resistance to weed invasion.

The purpose of this chapter is to evaluate both local topographic and soil effects on seedbed microclimate, as well as elevational effects on precipitation and temperature inputs within the Warm Springs Basin (WSB) test domain of the Boise Front Management Area (Figure, 17). Given the long-term disturbance history of this area, we suggest that existing plant community distributions represent the current status of ecological resilience and resistance to weed invasion, and that these patterns are consistent with long-term patterns of variability in seedbed microclimate.

In the previous chapter of this thesis, we explored topographic and soil effects on seedbed microclimate and how they might influence the relative establishment of two perennial bunchgrass species and cheatgrass. The specific objectives in this chapter are to use remote sensing and ground measurements to characterize perennial and annual plant distributions; estimate the actual distribution of topographic and soil variability at a landscape-management scale; evaluate the spatial distribution of seedbed microclimate and potential establishment response; and determine the extent to which microclimatic seedbed characteristics are linked to existing vegetation and ecological states in the Boise Front. We use similar modeling techniques to those presented in the previous chapter to assess whether RSI can serve as an effective bioassay for classifying vegetation communities for potential resilience and resistance to weed invasion in landscapes that are frequently disturbed by wildfire. We propose that this information could then be used to enhance ESD information for restoration management planning by quantifying microclimatic site characteristics that are correlated with ecological resilience and resistance.

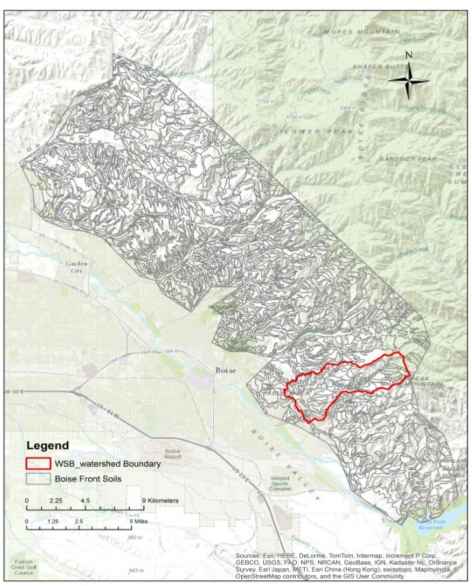


Figure 17: Warm Springs Basin within the BFMA.

Methods:

Study Area

The Warm Springs Basin (WSB) is a representative sub basin of the Boise Front Management Area (BFMA) north and east of Boise, Idaho (Figure 18). WSB is located at 43.67 degrees and -116.15. The basin encompasses 1327 ha with an elevation range from 900m in the lower foothills to 1700m at Lucky Peak. WSB is predominantly a westerly facing basin with equal percentages of north and south facing slopes. Ecological Sites in WSB fall mainly within Natural Resources Conservation Service (NRCS) Major Land Resource Area (MLRA) 10 (NRCS, 2006). The soils are clayey to fine loamy in lower elevations and fine loamy to coarse loamy as slope and elevation increase. Soils tend to fall between mesic and xeric moisture regimes with big sagebrush (*Artemisia tridentata* Nutt.) and antelope bitterbrush [*Purshia tridentata* (Pursh) DC.] shrub communities associated with bluebunch wheatgrass [*Pseudoroegneria spicata* (Pursh) ; Löve, Sandberg bluegrass (*Poa secunda* J. Presl) and Idaho fescue (*Festuca idahoensis* Elmer) in the understory (NRCS, 2006). These native species are the principle vegetation components of State 1 or Reference State for the STMs in the BFMA (Figure 18). The vegetation components of State 2 in the BFMA are primarily annual grasses with Sandberg bluegrass and root sprouting shrubs (Figure, 19; NRCS, 2006). Soils are various combinations of sand to sandy loam, loamy, clay loam and clay with shallow skeletal soils dominating above 1300 m and deeper soils below 1200m (NRCS, 2015b).

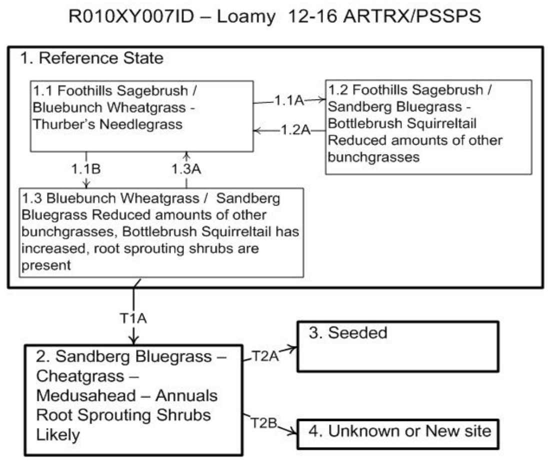


Figure 18: Sample State and Transition Model for Loamy ESDs in MLRA 10.

A process for determining land cover variability using remote sensing was applied with a focus on distinguishing perennial and annual dominated grass distributions by incorporating time series data, and multiple vegetation indices (Bradley and Mustard, 2005; Willis, 2015; Mitchell et al., 2015). This effort used Landsat 8 Thematic Mapper (TM) data to characterize vegetation patterns across the landscape as high resolution imagery tends to produce more accurate cover estimates (Willis, 2015). The Landsat 8 platform provided the most recent series of satellite imagery for the Boise Foothills with time series information extending from April 2013 to present (Glovis, 2015). Scene selection for this study focused on 2014 using Landsat 8 TM paths 41 and 42 and Row 30. Landsat 8 scenes were processed for the purpose of identifying relevant variables that relate to vegetation cover (Table 5). Vegetation index selection was based on indicators that are able to address cover variables such as vegetation type, soil composition, soil moisture and soil temperature relationships.

Preprocessing of each Landsat 8 scene is performed using Google Earth Engine. As part of the Landsat 8 preprocessing steps each image was calibrated for top-ofatmosphere reflectance. Target variables used in this study were categorized into cover types and species types. Predictor variables used in this study were extracted from Landsat 8 imagery using scenes from Rows 41, 42 and Path 30 with the GloVIS program (Glovis, 2015). A total of 39 scenes were identified but 12 were of any used based on cloud cover. Each photo point was used as a reference for selecting target pixels to be used in the classification. A “Grab-All” script was used to select pixels from each Landsat 8 scene within 1m of each photo point. These points were extracted to a table from which band math was applied to produce a range of vegetation indices that are related to identifying vegetation cover (Appendix A, Table 7). The final comparison incorporated 12 scenes with 15 reflectance bands and vegetation indices per pixel were associated with 190 points. Target classes used as target variables were based on cover type: annual, perennial, bare ground, and shrub. Species specific categories were also considered as target variables. Remotely sensed values used in the analysis are listed in table 8and topographic variables were used as predictors. A default of 500 bootstrap iterations was used.

Vegetation indices used in analysis	
Index	Formulation (R = reflectance, wavelengths in nm)
NDWI2	NDWI = (NIR - SWIR) / (NIR + SWIR)
L8 Band 1	Deep Blue
L8 Band 2	Blue
L8 Band 3	Green
L8 Band 4	Red
L8 Band 5	Near Infrared (NIR)
L8 Band 6	Mid Infrared (MIR)
L8 Band 7	Shortwave Infrared (SWIR)

L8 Band 8	Panchromatic
SAVI	SAVI = ((NIR - Red) / (NIR + Red + L)) x (1 + L)
NDVI	NDVI = ((NIR - Red)/(NIR + Red))
MSI	MSI = $P_{MIR} + P_{NIR}$
GEMI	GEMI=eta*(1-0.25*eta)-((Red-0.125)/(1-Red))
	eta=(2*(NIR^2-Red^2)+1.5*NIR+0.5*Red)/(NIR+Red+0.5)
GVI	GVI=-0.2848*Band1-0.2435*Band2-0.5436*Band3+0.7243*Band4+0.0840*Band5-1.1800*Band7
MSAVI2	MSAVI2 = (1/2)*(2(NIR+1)-sqrt($(2*NIR+1)^2$-8(NIR-Red)))
PVI	PVI=(NIR-a*Red-b)/(sqrt(1+a^2))
TSAVI	TSAVI=(s(NIR-s*Red-a))/(a*NIR+Red-a*s+X*(1+s^2))

Table 5: Indices Used in the Random Forests Cover Classification. L = 0.5, a = slope of the soil line, b =gradient of the soil line.

Field Sampling

Field sampling was conducted in late May and early June of 2014. Sample locations were determined using a stratified random sampling approach where 20 points were created for each soil polygon in the study area. The objectives for the field sampling were to capture as much diversity within each polygon as possible. Field samples consisted of photo points taken 2m above the surface as close to nadir as possible using a photo pole and a leveling bubble. Each photo was taken using a Nikon Coolpix 16 megapixel GPS enabled camera. Photos were processed using Sample Point software which was developed to classify vegetation based on a digital image (Crimmins and Crimmins, 2008). Photo point analysis focused on identifying specific grass species along with describing significant forb and shrub components. Soil and rocks were lumped together as bare ground. Plant litter was predominately from annual grass mortality and was composed principally of cheatgrass (*Bromus tectorum* L.), medusahead wildrye [*Taeniatherum caput-medusae* (L.) Nevski], 6-week fescue [*Vulpia octoflora* (Walter) Rydb.] and annual forbs. The dominant perennial litter was either bulbous bluegrass (*Poa bulbosa* L.) or Sandberg bluegrass (*Poa secunda* J. Presl). Each photo point was then classified based on dominant cover type.

Random Forests

The purpose of classifying the units into discrete Soil Mapping Units (SMUs) was to provide a structure in the data from which RSI could also be derived and also from which to compare to the current land cover. Vegetation cover classification was performed using random forests (Salford Predictive Modeler Software Suite version 7, Salford Systems, San Diego, CA) to determine which target variable derived from the field data best matched predictor variables produced from Landsat 8. We chose the random forests technique for its accuracy in ecological applications, automatic variable selection, and generation or an internal unbiased estimate of the generalization error (Breiman, 2001; Cutler et al., 2007). Advantages with random forests are that it provides the ability to determine the over-all importance of each variable in the decision tree model. Random forests is well suited to this due to its production of variable importance plots. Random forests use bootstrap sampling of datasets to “fit” the classification tree. Observations not include in the bootstrap sample are called out-of-bag observations. Each fitted classification tree is then used to predict the “out-of-bag” observations (OOB). Cross-validation is calculated using the out-of-bag observation to provide an R^2 derived from the OOB accuracy. This process is repeated until a final classification with cross-validation accuracy is produced.

RSI Model Development

ESD units are typically characterized in soil map units (SMUs) outlined by NRCS in the Soil Survey Geographic database (SSURGO) (USDA-NRCS, 2015b). Site specific ESD information is linked to individual components within SMUs and can be extracted from the SSURGO database (USDA-NRCS, 2015b). Each SMU can contain multiple components with associated ESDs. For subsequent modeling, only the largest of each component was used in the comparison. Soil parameter values necessary for running the SHAW model were extracted from the SSURGO database and appended to a primary reference table. Each SMU within the WSB was used as a bounding unit for each SHAW and hydrothermal model run. Bulk density and soil texture were extracted from the SSURGO database for the area of interest and appended to the input table. Slope, aspect and elevation for each polygon were obtained from a 10m DEM obtained from Inside Idaho (2015). WSB contained 63 individual SMUs that were modeled in this study. A look up table was developed using Arcmap Model Builder to provide a table with SMU specific inputs to be used by SHAW (Table 5). A Statistical Analysis Software (SAS; SAS Institute, Inc.) routine was used to create input files for each SHAW run with polygon-specific soil temperature, site and input files (Flerchinger et al., 2012). The initialization point for soil water content for each model run was estimated to be at a water potential of -1.5 MPa (Abu-Hamdeh and Reeder, 2000). Initial-condition soil-temperature values were estimated using air temperature from the previous two weeks before the start of each model run (Hasfurther et al., 1972). Starting time for each model run was July 15 of each year which allowed for 2.5 months for the model run to normalize (Flerchinger et al., 2013). Seedbed microclimate model runs were made for each year of a 31 year weather scenario in each polygon for the period Oct 1980 to Sep 2011 following the procedures described in the previous chapter.

Climate input data for the simulations were obtained from a combination of DAYMET and METdata (Thornton et al., 1997; Abatzoglou, 2013). DAYMET provides 1km gridded climate coverage of the lower 48 United States and certain parts of southern Canada and northern Mexico (Thornton et al., 2012). DAYMET data contains precipitation, solar radiation, air temperature and humidity (Thornton et. al., 2012). Wind speed data is derived from the METdata 4km gridded climate (Abatzoglou, 2013). Both data sets are periodically updated from a starting period of 1980 to present so provide an ongoing resource for continued inference (Thornton et al., 2012, Abatzoglou, 2013). SHAW modeled energy and water flux at the soil surface include absorbed solar radiation, long-wave radiation exchange and the stochastic transfer of heat and vapor as influenced by slope, aspect and latitude (Flerchinger and Hardegree, 2004). Twenty SMU-specific weather input files were created on a 1km grid to cover the entire WSB spatial domain. This information is then appended to the reference table. Key parameter fields for the model run are referenced in Table 6.

Component in the Field	**Alias Used in the Model**
• Key Field for linking back to SMU	• LinkMe
• Average Aspect for SMU	• AspMean

• Average Slope for SMU	• SlpMean
• Average Elevation for SMU	• ElevMean
• Dominant SMU series % Sand	• Sand
• Dominant SMU series % Silt	• Silt
• Dominant SMU series % Clay	• Clay
• Bulk Density for the SMU	• Bd
• Longitude	• Long
• Latitude	• Lat
• Solar noon	• SolNoon
• Identification of Reference Climate File	• Climate

Table 6: Input Variables For Bulk RSI Model Run.

SHAW model parameterization and output procedures were as described in the previous chapter. Hourly seedbed temperature and water potential outputs from the 31 year simulation within each SMU were used as input into the same hydrothermal models used for cheatgrass, bottlebrush squirreltail and Idaho fescue in the previous chapter and yielding the same monthly RSI parameters as a function of time period for each SMU. RSI values were estimated for each year, and seasonal values determined for the Oct-Nov fall period, Mar-May spring period, and growing season Oct-Jun. Parameters for each soil type in the study area were extracted and condensed into a look-up table that was referenced for building an individual SHAW input file for running the model. Subsequent outputs set for 2cm soil moisture and temperature values for each SMU were then used for calculating individual RSI values for each species.

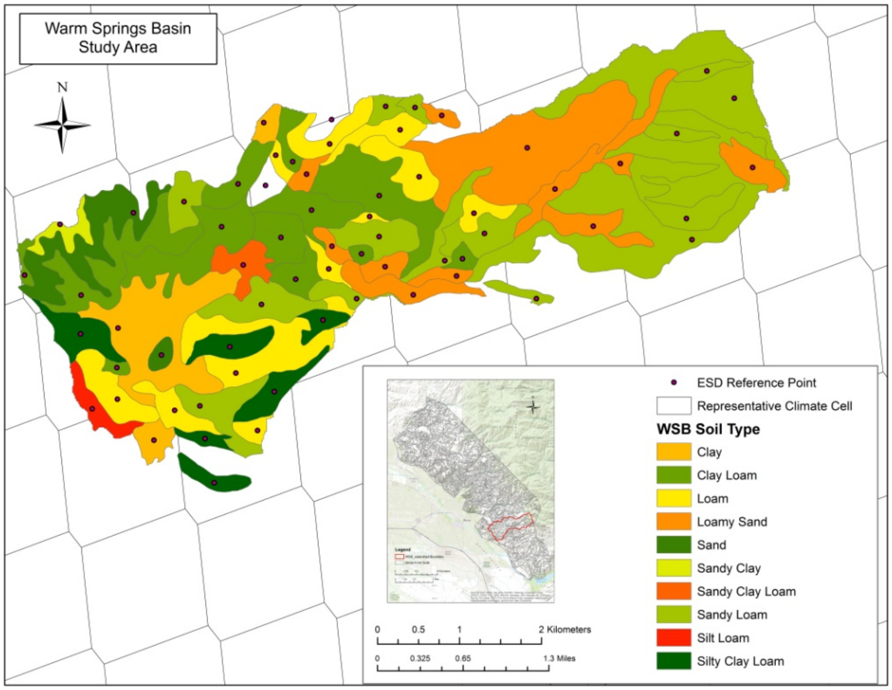


Figure 19: SMU Units And Overlapping Climate Cells Used In RSI Model For WSB.

Annual and seasonal RSI value categorization was based on hydrologic year (Oct to Sep) and divided into above-average, average and below-average years. For the 31 year record the 10 highest and ten lowest seasonally adjusted RSI values were averaged as estimators of below and above average year indices respectively. These periods were defined as good, bad and average RSI periods based arbitrarily on where they ranked in the 31 year spectrum of RSI values. Seasonal selection was based on the previous chapter where the fall and spring periods were identified as being the most important for germination rate and initial plant establishment. Each season was adjusted to focus on the most optimal periods for germination for all species. Based on the previous chapter, winter (Dec – Feb) had low over-all rates and were likely too cold to generate significant RSI values while summer periods (Jul-Sep) were too dry to contribute to either perennial or annual initial establishment.

Analysis focuses on comparing the established cover communities of perennial and annual vegetation from the remote sensing to microclimate indices based on seasonal RSI and conditions likely to occur in below-average, average and above-average establishment years. A stepwise regression Annual and perennial plant distributions were also evaluated relative to slope, aspect, elevation, and precipitation and air temperature gradients. The range of potential states for each soil type was identified based on the current cover and RSI site indices.

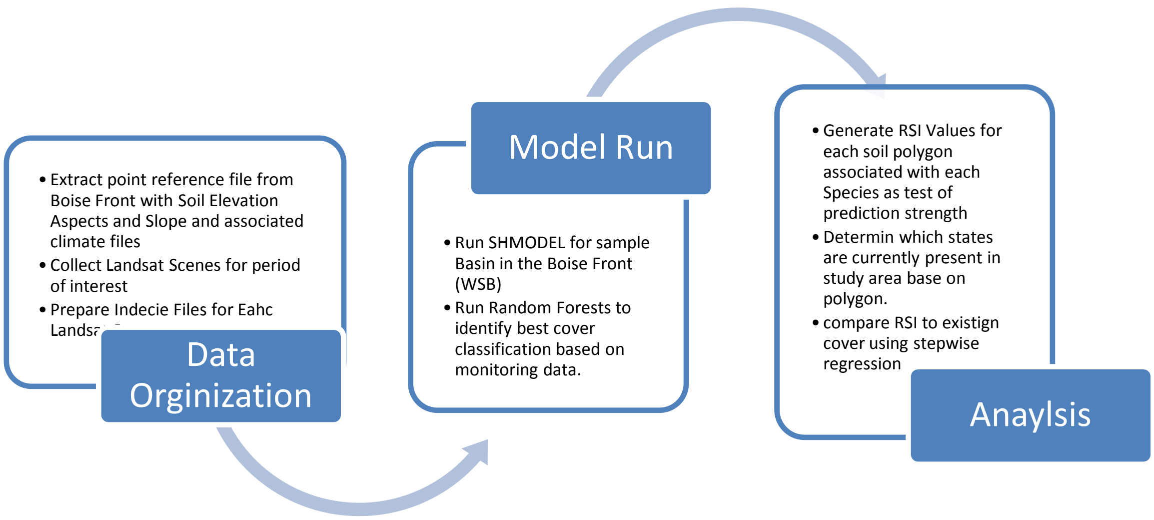


Figure 20: Generalized Methods Workflow.

Results

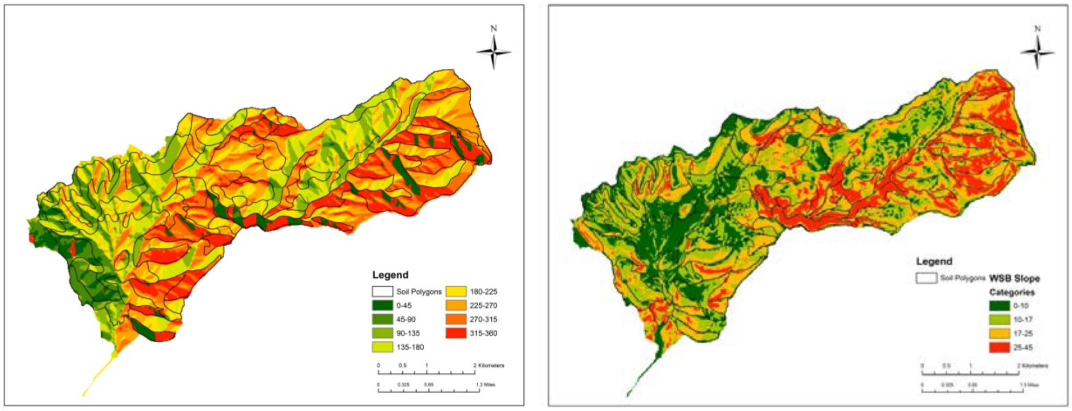


Figure 21: Slope and Aspect Distribution in WSB.

Averaged slopes were 7% to 30% with a majority of aspects in WSB south facing between 145 and 270 degrees (Figure 21). Slope aspect and elevation ranges tended to be less than actual due to averaging effects and size of individual SMU. Annual Precipitation averaged 275mm at 900m to 495mm at 1700m (Figure 22). Temperature Averages were the inverse of precipitation which ranged from an average of 10˚C at 900m to 6.85˚C at 1700m (Figure 22). The mid elevation point is used to characterize seasonal variability within the basin (Figure 23). Most precipitation occurred between October and June of each year with temperature ranging from -7˚C in January to 30˚C in July (Figure 22).

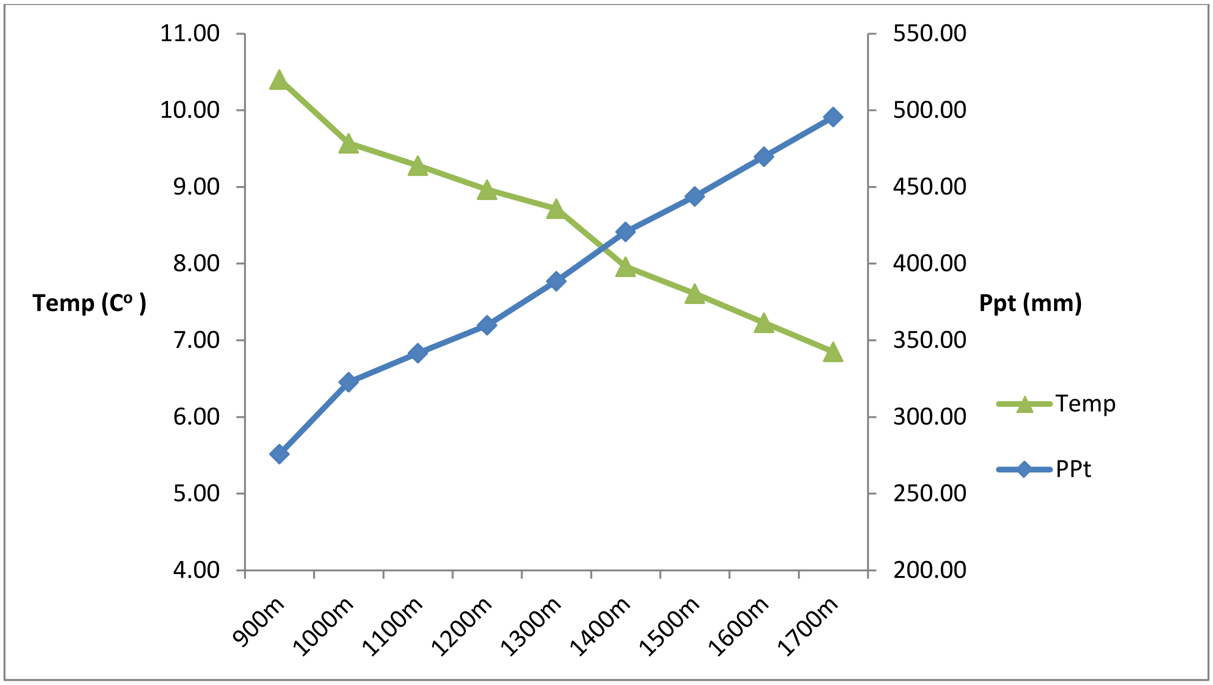


Figure 22: Right Axis Is Precipitation (Ppt) In Mm And Left Axis Is Average Temperature (C°) For WSB By Elevation Gradient. Elevation Increments On X Axis.

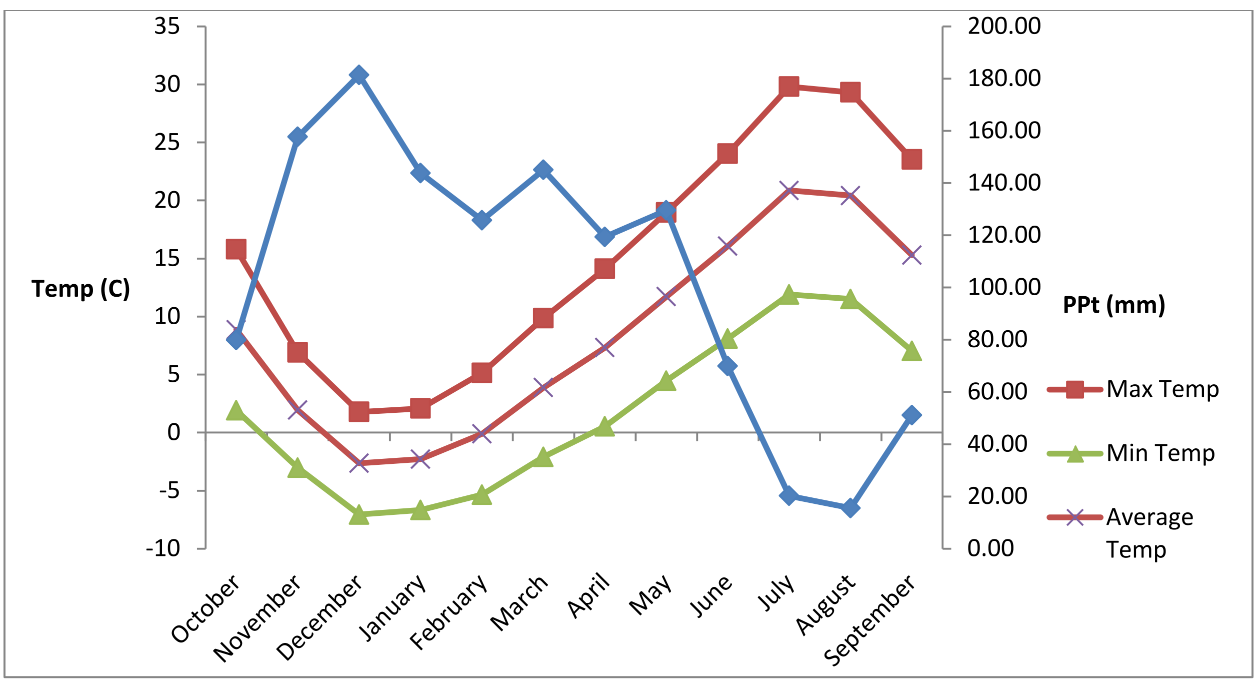


Figure 23: Seasonal Temperature Ranges For WSB At 1300m. Right Axis Is Precipitation (Ppt) And Left Axis Is Average Temperature (C) For WSB By Elevation Gradient. Elevation Increments On X Axis.

Predictor Variables	Annual Values	Predictor Variables	Perennial Values
41_248_NDWI2	100	41_248_NDWI	100
41_152_B1	65.81	42_207_MSI	65.14
41_207_B1	58.48	42_207_NDWI	56.78
41_152_B2	45.28	41_104_B3	52.25
41_42_239_SAVI	39.74	42_239_NDVI	45.07

Table 7: Random Forests Predictor Variables used in generating Annual and Perennial cover Maps. First number is the Path, the second number is the Julian Day, the third variable is the Band of Vegetation Index. NDWI2 = Normalized Difference between Water Index, NDWI = Normalized Difference between Water Index, NDVI = Normalized Difference between Vegetation Index, SAVI = Soil Adjusted Vegetation Index, B1 = Blue, B2 = Green, B3 = Red.

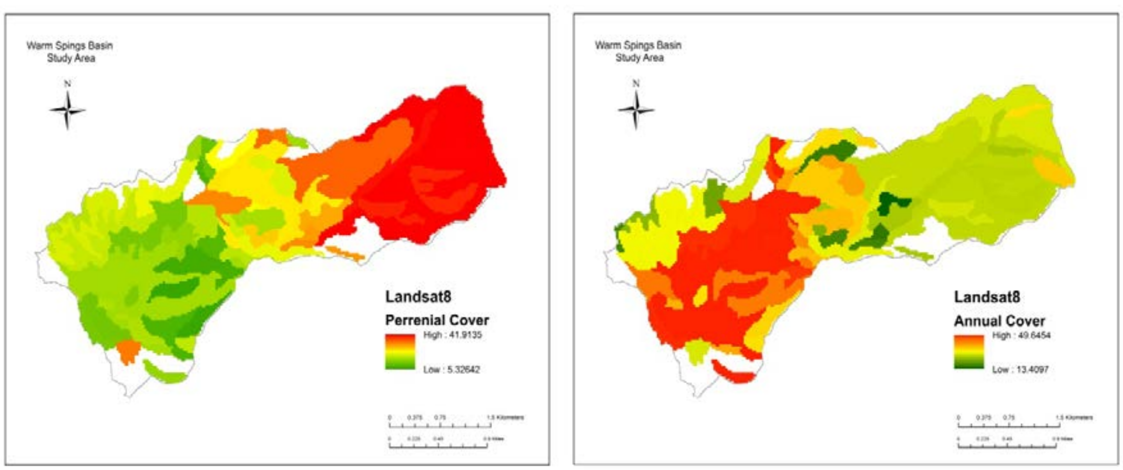


Figure 24: Cover Maps From Landsat 8 Classified Using Random Forests.

Random Forests

Random forests results for perennial and annual cover were consistently low. Perennial cover had an OOB of R^2 value (R^2= .35) with an RMSE of 0.13. Annual cover had slightly higher OOB R^2 value (R^2 = 0.38) with a RMSE of 0.23. Perennial cover was highest in elevations greater than 1300m. Annual cover tended to be highest in elevations lower than 1200m.

RSI classification of the 63 SMUs within WSB resulted in 31 years of RSI scenarios for each SMU. Annual RSI was assessed for the most and least optimal hydrologic 10 year periods with 11 annual periods in between. Typical "Good Year" RSI values ranged from .25 to .19 while "Bad Year" RSI values ranged .15 to .10 (Figure 25).

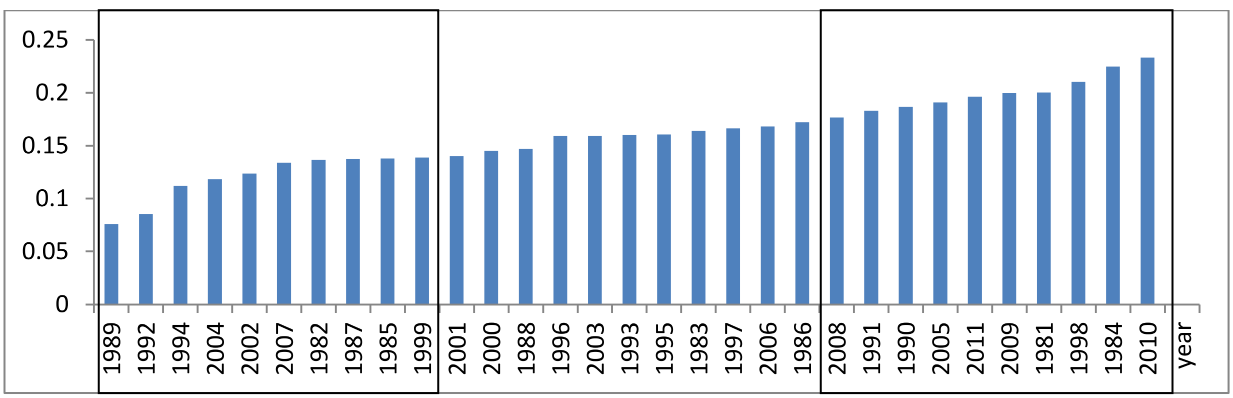


Figure 25: Averaged Annual RSI Range for all Species in WSB. Each Group is a ten year period sorted from lowest to highest to provide a ranking of Bad, Average, and Good RSI year.

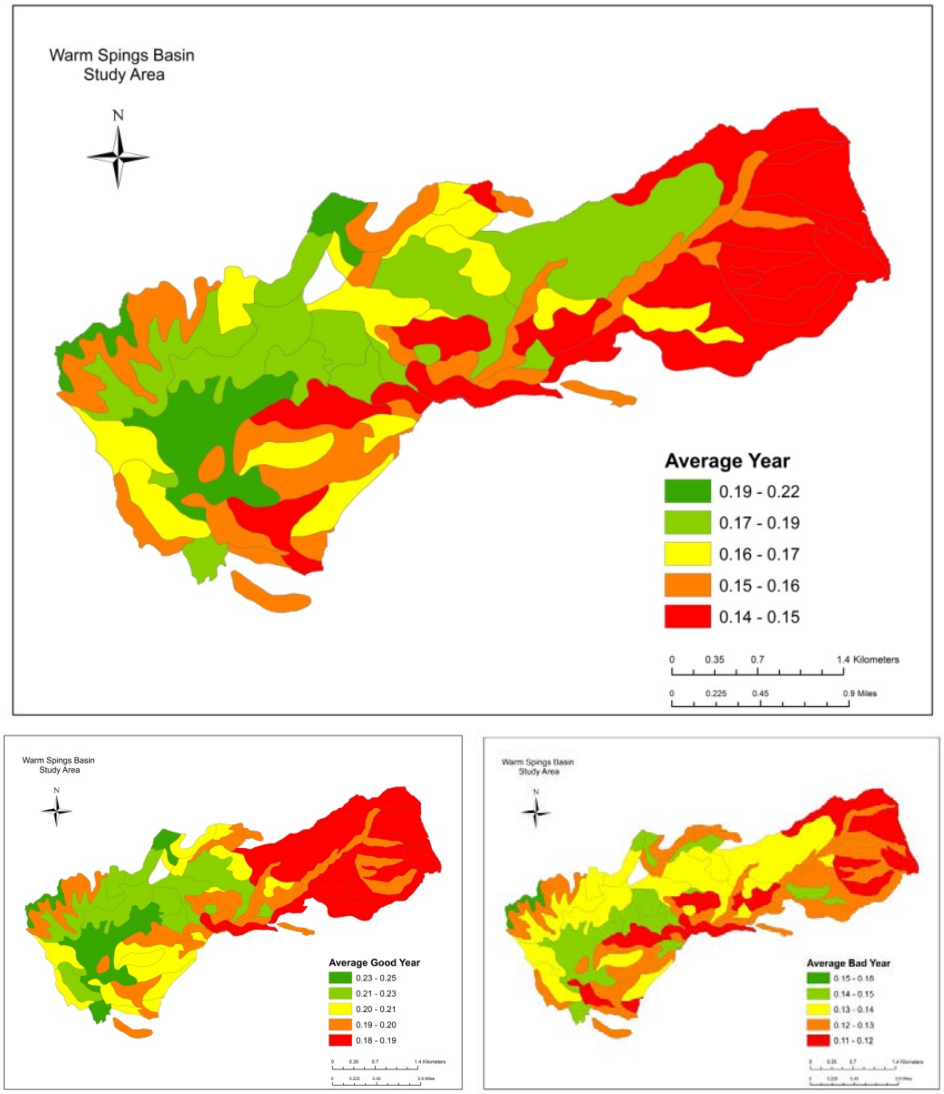


Figure 26: RSI distribution for Good, Average and Bad RSI years in WSB. Year is defined as October through June Period. July through September was not considered.

To determine existing relationships between seasonal or annual vegetation and topographic and RSI categories, two tests were utilized. A stepwise linear regression was conducted to predict which RSI period had the best relationship to the remote sensing data. Above average, average and below-average Fall, Spring and Annual RSI values of each species and an over-all average value for all species in target season and annual periods. A significance level of 0.15 was used as a minimum threshold for each independent variable to be included in the model. If the significance level was not met the variable was not included in the model. Significant topographic and RSI variables were only detected for perennial plant cover. Remote Sensing values for perennial cover are significantly associated with the above-average microclimatic classifications for the three species independent from each other. Overall adjusted R^2 values were 0.31 with an RMSE of 7.28 (Table 8).

Target Variable		R^2
Perennial Cover	Cheatgrass Good Yr	0.23
Perennial Cover	Squirreltail Good Yr	0.31
Perennial Cover	ID Fescue Good Yr	0.35
All Species Adjusted R^2	0.31	
All Species Adjusted RMSE	7.28 %	

Table 8: Results from regression model comparing Cover variables to RSI Values.

Discussion

Remote Sensing derived cover maps were only weakly associated with RSI and topographic categories (R^2 = 0.38 (Annual); R^2 = 0.35 (Perennial)) overall. There was a clear transition between upper elevation perennial plant communities and lower-elevation annual plant communities at an elevation of approximately 1200m in the remotely sensed data. This elevation is associated with an average precipitation threshold of 360mm and average annual temperature threshold of 9.0˚ C. There were also consistent spatial patterns in the lower elevation zone that appeared to be unrelated to precipitation and temperature gradients but consistent with microclimatic gradients caused by soils, and topography. Historically, the BFMA and WSB have been subjected to recurrent and frequent wildfire which has been documented for the previous 150 years (Figure 27). The cover maps only provide a current view of vegetation but given the recurrent fire history, they appear to reflect relative ecological resilience and resistance to weed invasion. Chambers et al., (2014) theorized that a precipitation threshold would exist based on elevation gradients, which appears to be the case here. The area above 1200m is currently in a disturbed but mostly perennial state and the lower elevation area is more significantly disturbed and in a mostly annual state. Our RSI data, however, are more finely tuned to topographic and soil effects on local microclimate within a given elevation zone. General elevation effects are also mirrored by topographic transitions where northerly aspects are also more resilient and resistant to weed invasion.

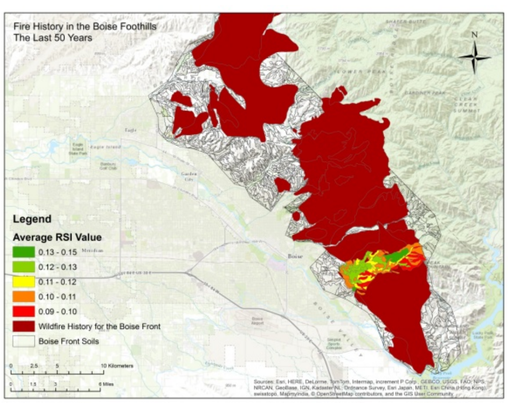


Figure 27: Recorded Fire History Extent Of The BFMA

Within a given elevation range, the higher and lower zones also have consistently different topography and soils. Upper elevations are predominantly coarser soils, have steeper slopes and a lower range of aspect variability than the lower elevation zone. In general, this tends to lower microsite favorability at higher elevation than would be indicated by gross precipitation and air temperature gradients as a function of elevation.

Our study makes several improvements over previous generic and broad-brush assessments of relative resistance and resilience such as characterized in Chambers et al., (2014). We have accounted for local topography and associated effects on soil microclimate, and also assigned a numerical value to reflect more site-specific soil microclimatic conditions. Local topography has similar relative effects as gross elevational changes, but our field sites represent only a fraction of the hypothetical topographic and soil categories explored in the previous chapter. As a comparison to the previous chapter, where topographic patterns were modeled for all scenarios, only 12 scenarios were relevant in WSB (Figure 28).

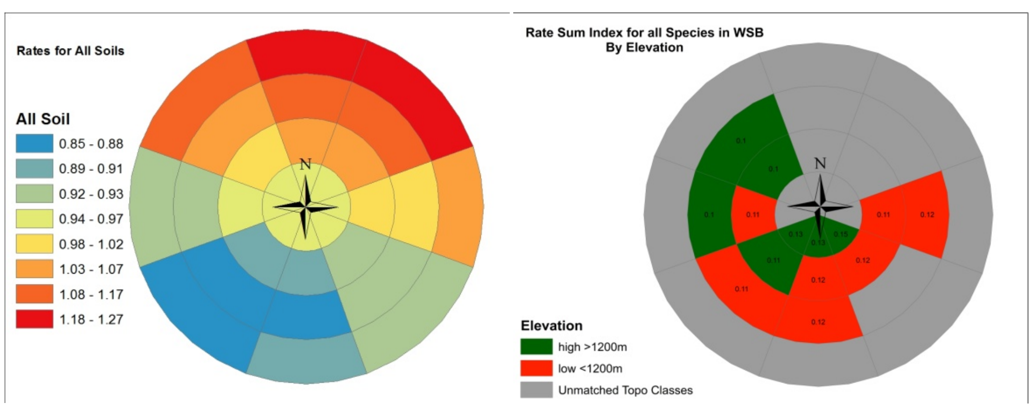


Figure 28: Comparison between topographic distribution of generalized RSI values for soils modeled in Chapter 2 and actual Topographic categories in Warm Springs Basin.

Conclusions and Management Implications

Guidelines are currently being developed for incorporating resistance and resilience concepts into the management decision making process (Miller et al., 2014; Chambers et al., 2014). The first step in this approach focuses on characterizing the current ecological state (Miller et al., 2014). RSI analysis can be used to supplement this information to also describe annual and seasonal variability in site favorability at a more detailed level than gross characterization of precipitation and air temperature. RSI assessments integrate site favorability into a bioassay for potential establishment response in an area that has frequent wildfire disturbance and re-establishment of plant communities through secondary succession. Assignment of RSI values can also be used to quantify annual variability in seedbed microclimate, to evaluate historical restoration success or failure after individual wildfire events, and perhaps in assigning transition probabilities for State and Transition Models for moving from weedy to perennial plant communities in restoration management applications (Hardegree et al., 2013). RSI values may also provide a more mechanistic way of classifying habitat suitability for species distribution models, and for more finely defining topographic variability in species distribution compared to the relatively broad remote sensing/climatological approach described by Bradley and Mustard (2005).

Chapter 4: Limitations to this Study and future applications

Soils

In this study, we characterized near surface properties that mostly have an impact on initial post-disturbance establishment. This is highly relevant for areas with a relatively frequent fire cycle caused by annual weeds such as cheatgrass. This methodology, however, can be expanded to look at lower soil processes and seasonal water relations that pertain more directly to maintenance and resistance to weed invasion in the perennial plant communities. One important aspect of invasive weed resistance is for perennial vegetation to mature sufficiently to exploit water and other soil resources at greater depths than are accessible by cheatgrass.

Remote Sensing

Development of the cover maps resulted in low over all R^2 values for both the annual and perennial cover estimates. While field data consisted of 200 photo points which were randomly distributed throughout the lower portion of the watershed, future approaches should stratify sample points within landsat 30m x 30m pixels within soil polygons. Landscape classification approaches that design the ground truth measurements based on where the actual distribution of pixels in the study area tend to be more successful at ensuring higher classification accuracies in a target area (Sankey and Glenn, 2011; Sankey et al., 2013). Further research should consider focusing ground truth efforts on locations within a broader range of elevation and precipitation gradients.

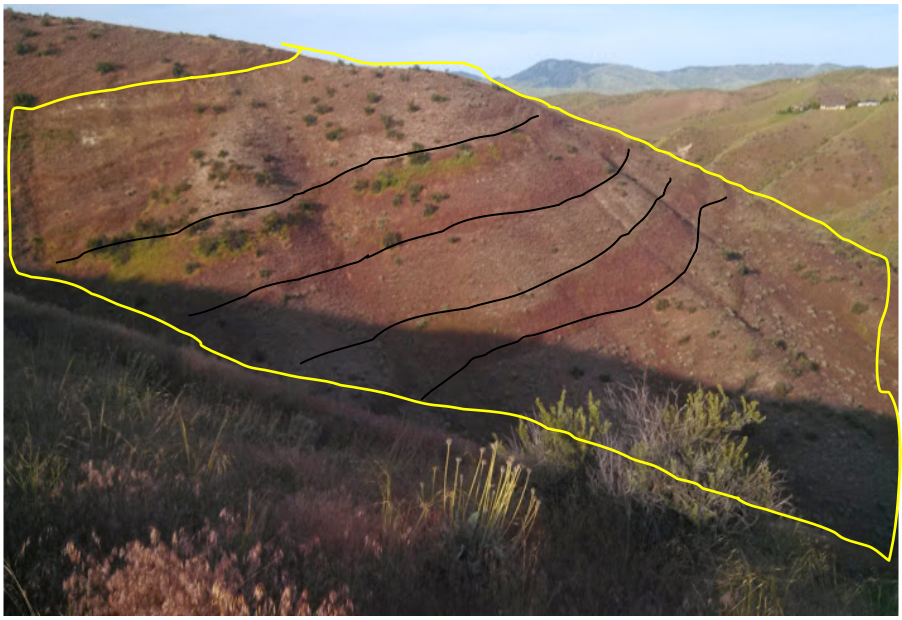


Figure 29: Example Sandy Loam Soil Unit In Foothills Terrain With Multiple Soil Components With Different Species Mixtures.

Soil Mapping Units

The RSI model currently operates on information derived from the dominant soil components of each SMU and utilizes a gridded climate data set. ESDs are frequently applied to SMUs which are composed of a complex of soils with different degrees of mixing with other units (Figure 30). To this extent RSI is intended to provide a general description of how favorable a site might be for early plant establishment. More accurate estimates of site specific RSI might be obtainable by considering a more detailed soil distribution within a given SMU, but that would require higher resolution soil maps than are currently obtainable. Gridded Climate variables also vary in their relative accuracy at different locations in the landscape (McEvoy et al., 2014). Precipitation and humidity in particular are difficult to accurately estimate in complex terrain (McEvoy et al., 2014). Better weather information and/or validation of the gridded/modeled datasets that we used would also improve the accuracy of RSI estimates across the landscape.

Species

Species selection for the RSI index was based on their relative abundance in the region but also to provide a wide range of potential germination response among annual and perennial bunchgrass species (Hardegree, 2015). The field monitoring identified a number of other perennial and annual plant species and evaluation of additional species-specific hydrothermal response and RSI indices might provide further insights about plant response as a function of topography and soil type (Reisner et al., 2013). One assumption is that by considering three species with relatively slow medium and fast germination rates the spectrum of biological response to the microclimates is captured. This ratio is consistent regardless of whether or not the year is considered a wet or dry year (Figure 30).

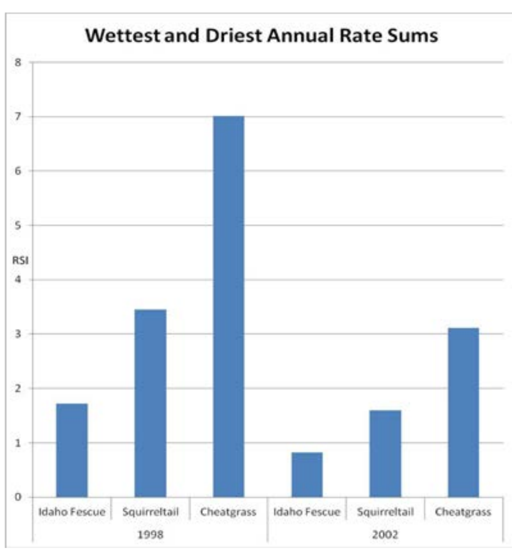


Figure 30: Wet and Dry Annual RSI Comparisons of Each Species.

Applications

Miller et al., (2014) outlined a method for determining the most ideal treatments for sagebrush restoration. RSI values can potentially improve this process by characterizing the relative resilience of the site to weed invasion. Chambers et al. (2014) proposed using four strategies to prioritize management areas and to identify appropriate management actions: protection, prevention, restoration, and monitoring and adaptive management. RSI can be used to supplement these strategies since they can inform managers of more site specific conditions of resistance and resilience components.

- Protection of an ecosystem is focused on sustaining or improving resilience and resistance by eliminating or minimizing factors that create stress (Brooks and Chambers, 2011). RSI can inform managers of what species may have higher potential for establishing in a given ecosystem such as salt desert or Wyoming big sagebrush. Cheatgrass typically has a high RSI value and can take advantage of almost any micro environmental condition. Successful management of cheatgrass impacted areas probably requires continuing and recurrent cheatgrass control until desirable perennial components have achieved sufficient size to be resistant to cheatgrass invasion.
- Prevention involves increasing both resilience and resistances of systems that have not crossed an undesirable ecological threshold, but that are otherwise high risk (Miller et al., 2013). As RSI values are dependent on weather variability, potential effects from climate change can be analyzed to provide a mechanistic description of areas that may be under higher risk in the future. In the BFMA, north slopes and higher elevations

typically can recover with relatively little management intervention. RSI values can be used to determine elevation, topography and soil thresholds for potential risk reduction.

- Restoration efforts are typically focused on improving the resilience and resistance of a disturbed, invaded or otherwise degraded site by recreating the diversity and functionality of the plant community (Chambers et al., 2014). Lower elevation sites, in general may be less resilient and resistant, but in any given year, the microclimatic scenario may still be conducive to initial restoration success. Incorporation of seasonal forecasting may facilitate prediction of these potential restoration years so that resources can be targeted more efficiently only when success is feasible (Hardegree et al., 2012). RSI values can be used to score a given site and inform planners of a species potential ability to perform at a given site based on the physical properties and what kind of sustained weather conditions may be necessary to reach a resilient vegetation state.
- A final critical component to ecosystem restoration is the monitoring and adaptation of management practices (Chambers et al., 2014). RSI can contribute to monitoring efforts by adding an additional quantified index of ecosystem microclimatic status to the monitoring process. Both long and short term monitoring strategies can use RSI as a physical value that is linked to both the historical probabilities of vegetation state transitions, and the potential restoration options under both current and potential future climate conditions. Weather inputs are a primary component to the RSI model and are a principal driver of restoration success or failure (Hardegree, 2011). Weather variability may also determine the relative probability of success in a given year, and the

need for specific adaptive management practices to maintain a plant community in a long-term trajectory toward a more desirable state.

Further Research

The RSI model offers insight towards species potential performance within a given context of an ESD. This model focuses on the first stage of life for any plant species and provides a rate at which germination can occur. This model does not address mortality nor does it directly link to other growth models. Further research can continue focusing on addressing what those potential species specific mortality evens could entail and be further linked to a growth model that does provide some connection to established communities. Probable community development can be explored using this method and provide managers with more informed expectations about their restoration efforts.

References

Abatzoglou, J.T. (2013) Development of gridded surface meteorological data for ecological applications and modeling. International Journal of Climatology. DOI: 10.1002/joc.3413.

Abu-Hamdeh, N.H., and R.C. Reeder. 2000. Soil thermal conductivity: Effects of density, moisture, salt concentration, and organic matter. Soil Sci. Soc. Am. J. 64:1285–1290.

Ada County. 2010. Ada County Hazard Vulnerability Analysis. https://adacounty.id.gov/Portals/Accem/Doc/PDF/Ada_County_HVA_secure.pdf Accessed 4-28-2015.

Bradley, B. A. 2009. Regional analysis of impacts of climate change on cheatgrass invasion shows potential risk and opportunity. Global Change Biol. 15: 196_208.

Bradley, B. A., and J. F. Mustard. 2005. Identifying land cover variability distinct from land cover change: cheatgrass in the Great Basin. Remote Sensing of Environment 94:204–213.

Briske, D. D., S. D. Fuhlendor, and E. E. Smeins. 2005. State-and-transition models, thresholds, and rangeland health: a synthesis of ecological concepts and perspectives. Rangeland Ecology & Management 58:1–10. BioOne

Brooks ML and Chambers JC. 2011. Resistance to invasion and resilience to fire in desert shrublands of North America. Rangeland Ecol Manage 64:431–8.

Bullied, W. J., Van Acker, R. C. and Bullock, P. R. 2012a. Hydrothermal modeling of seedling emergence timing across topography and soil depth. Agron. J. 104: 423_436.

Bullied, W.J., Van Acker, R.C., Bullock, P.R., 2012b. Review: Microsite characteristics influencing weed seedling recruitment and implications for recruitment modeling. Can. J. Plant Sci. 92 (4), 627–650.

Call, C. A., and B. A. Roundy. 1991. Perspectives and processes in revegetation of arid and semiarid rangelands. Journal of Range Management 44:543–549.

Chambers, Jeanne C.; Pyke, David A.; Maestas, Jeremy D.; Pellant, Mike; Boyd, Chad S.; Campbell, Steven B.; Espinosa, Shawn; Havlina, Douglas W.; Mayer, Kenneth E.; Wuenschel, Amarina. 2014. Using resistance and resilience concepts to reduce impacts of invasive annual grasses and altered fire regimes on the sagebrush ecosystem and greater sage-grouse: A strategic multi-scale approach. Gen. Tech. Rep. RMRS-GTR-326. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 73 p.

Crimmins MA, TM Crimmins. 2008. Monitoring plant phenology using digital repeat photography. Environmental Management 41:949-958.

Eckert, R. E., F. F. Peterson, M. S. Meurisse, and J. L. Stephens. 1986. Effects of soil-surface morphology on emergence and survival of seedlings in big sagebrush communities. Journal of Range Management 39:414–420.

Egli, D. B., and T. M. Tekrony. 1996. Seedbed conditions and prediction of field emergence of soybean seed. Journal of Production Agriculture 9:365–370.

Flerchinger, G. N, (2000) The Simultaneous Heat and Water (SHAW) Model: Technical Documentation. USDA ARS Technical Report NWRC 2000-09.

Geroy, I.J., Gribb, M.M., Marshall, H.P., Chandler, D.G., Benner, S.G. and McNamara, J.P. (2011), Aspect influences on soil water retention and storage. Hydrol. Process., 25: 3836–3842. doi: 10.1002/hyp.8281

Hardegree, S. P., and A. H. Winstral. 2006. Predicting germination response to temperature. II. Three-dimensional regression, statistical gridding and iterative probit optimization using measured and interpolated-subpopulation data. Annals of Botany 98:403–410.

Hardegree, S. P., Flerchinger, G. N. and VanVactor, S. S., 2003. Hydrothermal Germination Response and the development of probabilistic germination profiles. Ecological Modeling 167:305-322.

Hardegree, S. P., T. A. Jones, B. A. Roundy, N. L. Shaw, and T. A. Monaco. 2011. Assessment of range planting as a conservation practice. In: D. D. Briske [ED.]. Conservation benefits of rangeland practices: assessment, recommendations, and knowledge gaps. Lawrence, KS, USA: Allen Press. p. 171–212.

Hardegree, S.P., J. Cho and J.M. Schneider. 2012. Weather variability, ecological processes, and optimization of soil micro-environment for rangeland restoration. In: T.A. Monaco and R.L. Sheley (Eds.). Invasive Plant Ecology and Management: Linking Processes to Practice. CAB International, Wallingford, Oxon. pp. 107-121.

Hardegree, S. P., S. S. Van Vactor, F. B. Pierson, and D. E. Palmquist. 1999. Predicting variable-temperature response of non-dormant seeds from constant-temperature germination data. Journal of Range Management 52:83–91.

Hasfurther, V., R. D. Burman, and J. Nunn. 1972. A model for Predicting Soil Temperature from Air Temperature. Technical report No. 178. U.S. International Biological Program

Hernandez, A. and R. D. Ramsey. 2013. A Landscape Similarity Index: Multitemporal Remote Sensing to Track Changes in Big Sagebrush Ecological Sites. Rangeland Ecology & Management 66(1):71-81. doi: http://dx.doi.org/10.2111/REM-D-11-00195.1

Immitzer M, Atzberger C, Koukal T. Tree species classification with random forest using very high spatial resolution 8-band WorldView-2 satellite data. Remote Sensing. 2012; 4(9), pp. 2661-2693. doi:10.3390/rs4092661. http://www.mdpi.com/2072-4292/4/9/2661

James, J. J. and T. Svejcar. (2010) Limitations to Postfire Seedling Establishment: The Role of Seeding Technology, Water Availability, and Invasive Plant Abundance. Rangeland Ecology & Management: July 2010, Vol. 63, No. 4, pp. 491-495.

Inside Idaho. 2015. Available at: https://insideidaho.org/popular_data.html. Accessed 15 March 2015.

Jordan, G. L. 1981. Range seeding and brush management on Arizona rangelands. Jordan City, AZ, USA: Agricultural Experiment Station University of Arizona College of Agriculture. Bulletin T81121. 88 p.

Knight, J.F., R.L. Lunetta, J. Ediriwickrema, and S. Khorram, 2006. Regional Scale Land-Cover Characterization using MODIS-NDVI 250 m Multi-Temporal Imagery: A Phenology Based Approach. GIScience and Remote Sensing, 43(1), 1-23.

Maas, S.J. 1988. Using satellite data to improve model estimates of crop yield. Agronomy Journal. 80: 655-662.

Mellor, A., Haywood, A., Stone C., Jones, S. 2013. The performance of random forests in an operational setting for large area sclerophyll forest classification. Remote Sensing. 5(6), pp. 2838-2856. doi: 10.3390/rs5062838. http://www.mdpi.com/2072-4292/5/6/2838

McEvoy, D.J., Mejia, J.F., and J.L. Huntington. (2014). Use of an Observation Network in the Great Basin to Evaluate Gridded Climate Data. Journal of Hydrometeorology, 15, 19131931. doi:10.1175/JHM-D-14-0015.1

McDonald, J.H. 2014. Handbook of Biological Statistics (3rd ed.). Sparky House Publishing, Baltimore, Maryland. http://www.biostathandbook.com/

Miller, R. F. Chambers, J. C. Pyke, D. A., Pierson, F. B. and Williams, C. J. 2013. A review of fire effects on vegetation and soils in the Great Basin Region: response and ecological site characteristics. Gen. Tech. Rep. RMRS-GTR-308. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 126 p.

Miller, Richard F.; Chambers, Jeanne C.; Pellant, Mike. 2014. A field guide for selecting the most appropriate treatment in sagebrush and piñon-juniper ecosystems in the Great Basin: Evaluating resilience to disturbance and resistance to invasive annual grasses, and predicting vegetation response. Gen. Tech. Rep. RMRS-GTR-322-rev. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 68 p.

Mitchell, J.J., Shrestha, R., Spaete, L. and Glenn, N. 2015. Combining Airborne Hyperspectral and LiDAR dat across local sites for upscaling shrubland structural information: Lesons for HyspIRI, Remote sensing of Environment. http://dx.doi.org/10.1016/j.rse.2015.04.015

Moeslund, J. E., Arge, L. Bøcher, P. K. Dalgaard, T., Odgaard, M. V., Nygaard, B. and Svenning, J. C. 2013. Topographically controlled soil moisture is the primary driver of local vegetation patterns across a lowland region. Ecosphere 4:art91. http://dx.doi.org/10.1890/ES13-00134.1

Moseley, K., Shaver, P. L., and Bestelmeyer, B. T. 2010. Ecological Site Development: A Gentle Introduction. Rangelands Vol. 32, No. 6, pp. 16-22. doi: http://dx.doi.org/10.2111/RANGELANDS-D-10-00092.1

Ogle, D., L. St. John, J. Cornwell, M. Stannard, and L. Holzworth. 2008. Pasture and range seedings: planning-installation-evaluation-management. Boise, ID, USA: USDA-NRCS. Technical Note PM-TN-10. 36 p.

Peters, D. P. C. 2000. Climatic variation and simulated patterns in seedling establishment of two dominant grasses at a semi-arid-arid grassland ecotone. Journal of Vegetation Science 11:493–504.

Reisner M. D., Grace, J. B., Pyke, D. A., and Doescher P. S. 2013. Conditions favoring Bromus tectorum dominance of endangered sagebrush steppe ecosystems. Journal of Applied Ecology 50, 1039-1049

Roundy, B. A., and C. A. Call. 1988. Revegetation of arid and semiarid rangelands. In: P. T. Tueller [ED.]. Vegetation science applications for rangeland analysis and management. Dordrecht, Netherlands: Kluwer Academic Publishers. p. 607–635.

Roundy, B. A., and S. H. Biedenbender. 1996. Germination of warm-season grasses under constant and dynamic temperatures. Journal of Range Management 49:425-431.

Roundy, B. A., V. K. Winkel, H. Khalifa, and A. D. Matthias. 1992. Soil water availability and temperature dynamics after one-time heavy cattle trampling and land imprinting. Arid Soil Research and Rehabilitation 6:53–69.

Sankey, T, and N Glenn. 2011. Landsat-5 TM and LiDAR Fusion for Sub-Pixel Juniper Tree Cover Estimates in a Western Rangeland. Photogrammetric Engineering & Remote Sensing 77 (12): 1241–48.

Sankey, T, R Shrestha, J B Sankey, S Hardegree, and E Strand. 2013. Lidar-Derived Estimate and Uncertainty of Carbon Sink in Successional Phases of Woody Encroachment. Journal of Geophysical Research: Biogeosciences 118 (3): 1144–55.

Seyfried, M. S., G. N. Flerchinger, C. L. Hanson, M. Murdock, and S. Van Vactor, Long-term microclimate database, Reynolds Creek Experimental Watershed, Idaho, USA, Tech. Bull. NWRC 2000-7, 29 pp., Northwest Watershed Res. Cent., Agric. Res. Serv., U.S. Dep. of Agric., Boise, Idaho, 2000a.

Sheley, R. L., J. M. Mangold, and J. L. Anderson. 2006. Potential for successional theory to guide restoration of invasive-plant-dominated rangeland. Ecological Monographs 76:365–379.

Sheley, R., J. Mangold, K. Goodwin, and J. Marks. 2008. Revegetation guidelines for the Great Basin: considering invasive weeds. Washington, DC, USA: USDA-ARS. ARS-168. 60 p.

Smith, T. J., J. P. McNamara, A. N. Flores, M. M. Gribb, P. S. Aishlin, S. G. Benner, Small soil storage capacity limits benefit of winter snowpack to upland vegetation, Hydrological Processes, 2011, 25, 25, 3858

Thornton, PE, Thornton, M. M., Mayer, B.W., Wilhelmi, N., Wei, Y., Cook, R. B. (2012) DAYMET: Daily surface weather on a 1 km grid for North America,1980 - 2008. Acquired online (http://daymet.ornl.gov/) on [15/10/2012] from Oak Ridge National Laboratory Distributed Active Archive Center, Oak Ridge, Tennessee, U.S.A. doi:10.3334/ORNLDAAC/DAYMET_V2.

USDA-NRCS. 2015a. National soil survey handbook, title 430-VI. Available online. Accessed 15 March 2015. Available at: https://esis.sc.egov.usda.gov/Default.aspx.

USDA-NRCS. 2015b. Soil survey geographic SSURGO database NRCS soils. Available at:http://soils.usda.gov/survey/geography/ssurgo/. Accessed 15 March 2015

USDA-NRCS. 2006. Land Resource Regions and Major Land Resource Areas of the United States, the Caribbean, and the Pacific Basin. U.S. Department of Agriculture Handbook 296.

Western Regional Climate Center (WRCC), 2015: Boise Air Terminal, Idaho (101022). [Available online at http://wrcc.dri.edu/cgi-bin/cliMAIN.pl?id1022

Westoby, M., B. Walker, and I. Noy-Meir. 1989. Opportunistic management for rangelands not at equilibrium. Journal of Range Management 42:266–274.

Wood, M. K., R. E. Eckert, W. H. Blackburn, and F. F. Peterson. 1982. Influence of crusting soil surfaces on emergence and establishment of crested wheatgrass, squirreltail, thurber needlegrass and fourwing saltbush. Journal of Range Management 35:282–287.

Zouhar, K. 2003. Bromus tectorum. In: Fire Effects Information System, [Online]. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Fire Sciences Laboratory (Producer). Available: http://www.fs.fed.us/database/feis/ [2015, February 6].

Appendix A: Tables and Figures

Tables

Table 1: Input Parameters used for Soil types

Soil	Bulk Density	Sand	Silt	Clay	Slope: 4 classes	Aspect: 8 Classes
Clay	1740	22	32	46	0, 15, 30, 45	0,45,90, 135, 180, 225, 270, 315
Loam	1180	35	45	20	0, 15, 30, 45	0,45,90, 135, 180, 225, 270, 315
Silt Loam	1510	26	55	19	0, 15, 30, 45	0,45,90, 135, 180, 225, 270, 315
Sand	1310	88	10	2	0, 15, 30, 45	0,45,90, 135, 180, 225, 270, 315

Table 2: Overall Spatial Variances for Species and Soils over all topographic categories. BRTE = Cheatgrass, ELEL = Squirrel Tail, FEID = Idaho Fescue.

Spp	Soil	*Variance*
BRTE	Sand	0.011952
BRTE	Silt Loam	0.016653
BRTE	Loam	0.018628
BRTE	Clay	0.019805
ELEL	Sand	0.003799
ELEL	Silt Loam	0.004394
ELEL	Loam	0.005531
ELEL	Clay	0.006156
FEID	Sand	0.000694
FEID	Silt Loam	0.000949
FEID	Loam	0.001041
FEID	Clay	0.00109

Table 3: Soil Results

Tukey's Studentized Range HSD Test For Soils				
Alpha	0.05			
Error Degrees of Freedom	108522			
Error Mean Square	0.015855			
Critical Value of Studentized Range	3.6332			
Comparisons significant at the 0.05 level are indicated by ***				
soil Comparison	Difference Between Means	Simultaneous 95% Confidence Limits		
clay-sand	0.029769	0.027028	0.03251	***
clay-silt-loam	0.036467	0.033743	0.039192	***
clay-loam	0.037255	0.03453	0.039979	***
sand-clay	-0.029769	-0.03251	-0.02703	***

sand-silt-loam	0.006699	0.003958	0.00944	***
sand-loam	0.007486	0.004745	0.010227	***
silt-loam-clay	-0.036467	-0.039192	-0.03374	***
silt-loam-sand	-0.006699	-0.00944	-0.00396	***
silt-loam-loam	0.000787	-0.001937	0.003512	
loam-clay	-0.037255	-0.039979	-0.03453	***
loam-sand	-0.007486	-0.010227	-0.00475	***
loam-silt-loam	-0.000787	-0.003512	0.001937	

Table 4: Difference between Species from Tukey HSD test

Differences between species		
Alpha	0.05	
Error Degree of Freedom	108522	
Error Mean Square	0.015855	
Critical Value of Studentized Range	3.31454	
Minimum Significant Difference	0.0022	
Species	Mean	N
BRTE: Cheatgrass	0.3461544	37374
ELEL: Squirrel tail	0.2577978	37374
FEID: Idaho Fescue	0.1733004	37374

Table 5: Example of Warm Springs Basin reference table for SHMODEL

Vegetation indices used in analysis	
Index	Formulation (R = reflectance, wavelengths in nm)
NDWI2	NDWI = (NIR - SWIR) / (NIR + SWIR)
L8 Band 1	Deep Blue
L8 Band 2	Blue
L8 Band 3	Green
L8 Band 4	Red
L8 Band 5	Near Infrared 1
L8 Band 6	SWIR: Shortwave Infrared
L8 Band 7	SWIR: Shortwave Infrared
L8 Band 8	Panchromatic
SAVI	SAVI = ((NIR - Red) / (NIR + Red + L)) x (1 + L)
NDVI	NDVI = ((NIR - Red)/(NIR + Red))
MSI	
GEMI	GEMI=eta*(1-0.25*eta)-((Red-0.125)/(1-Red))
	eta=(2*(NIR^2-Red^2)+1.5*NIR+0.5*Red)/(NIR+Red+0.5)
GVI	GVI=-0.2848*Band1-0.2435*Band2-0.5436*Band3+0.7243*Band4+0.0840*Band5-1.1800*Band7
MSAVI2	MSAVI2 = (1/2)*(2(NIR+1)-sqrt((2*NIR+1)^2-8(NIR-Red)))
PVI	PVI=(NIR-a*Red-b)/(sqrt(1+a^2))

TSAVI	TSAVI=(s(NIR-s*Red-a))/(a*NIR+Red-a*s+X*(1+s^2))

Table 5: Indices Used in the Random Forests Cover Classification

Table 6, Input variables for Bulk RSI Model Run.
Required Input Fields for running RSI Model:
*Soil Mapping Unit (SMU)

Component in the Field	**Alias Used in the Model**
• Key Field for linking back to SMU	• LinkMe
• Average Aspect for SMU	• AspMean
• Average Slope for SMU	• SlpMean
• Average Elevation for SMU	• ElevMean
• Dominant SMU series % Sand	• Sand
• Dominant SMU series % Silt	• Silt
• Dominant SMU series % Clay	• Clay
• Bulk Density for the SMU	• Bd
• Longitude	• Long
• Latitude	• Lat
• Solar noon	• SolNoon
• Identification of Reference Climate File	• Climate

Table 7: Random Forests Predictor Variables used in generating Annual and Perennial cover Maps.

Predictor Variables	Annual Values	Predictor Variables	Perennial Values
L8_41_248_NDWI2	100	L8_41_248_NDWI	100
L8_152_B1	65.8107	42_207_MSI	65.1385
L8_207_B1	58.4756	42_207_NDWI	56.7798
L8_152_B2	45.2753	41_104_B3	52.2476
L8_42_239_SVI	39.7405	42_239_NDVI	45.0678

Table 8: Results from regression model comparing Cover variables to RSI Values.

Target Variable		R^2
Perennial Cover	Cheatgrass Good Yr	0.23
Perennial Cover	Squirreltail Good Yr	0.31
Perennial Cover	ID Fescue Good Yr	0.35
Adjusted R^2	0.31	
RMSE	7.28	

The REG Procedure
Model: MODEL1
Dependent Variable: Perrenial_Cover

Number of Observations Read 63
Number of Observations Used 63

Stepwise Selection: Step 1

Variable BRTE_Hydro_Good Entered: R-Square = 0.2317 and C(p) = 9.9366

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	1109.64740	1109.64740	18.40	<.0001
Error	61	3679.02995	60.31197		
Corrected Total	62	4788.67736			

Variable	Parameter Estimate	Standard Error	Type II SS	F Value	Pr > F
Intercept	73.03362	12.70124	1994.14703	33.06	<.0001
BRTE_Hydro_Good	-156.04368	36.37939	1109.64740	18.40	<.0001

Bounds on condition number: 1, 1

Stepwise Selection: Step 2

Variable ELEL_Hydro_Good Entered: R-Square = 0.3093 and C(p) = 4.9720

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	2	1481.33529	740.66764	13.44	<.0001
Error	60	3307.34207	55.12237		

Corrected Total 62 4788.67736

Variable	Parameter Estimate	Standard Error	Type II SS	F Value	Pr > F
Intercept	63.58259	12.67624	1386.83112	25.16	<.0001
BRTE_Hydro_Good	-352.60056	83.30188	987.60716	17.92	<.0001
ELEL_Hydro_Good	387.20653	149.11365	371.68788	6.74	0.0118

Bounds on condition number: 5.7369, 22.947

Stepwise Selection: Step 3

Variable FEID_Hydro_Good Entered: R-Square = 0.3470 and C(p) = 3.5943

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	1661.59810	553.86603	10.45	<.0001
Error	59	3127.07925	53.00134		
Corrected Total	62	4788.67736			

Variable	Parameter Estimate	Standard Error	Type II SS	F Value	Pr > F
Intercept	55.21600	13.23199	922.92522	17.41	0.0001
FEID_Hydro_Good	646.17085	350.37872	180.26282	3.40	0.0702
BRTE_Hydro_Good	-434.72599	93.03362	1157.27945	21.83	<.0001
ELEL_Hydro_Good	303.71566	153.06491	208.67478	3.94	0.0519

Bounds on condition number: 7.4419, 56.231

All variables left in the model are significant at the 0.1500 level.

No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Selection

Step	Variable Entered	Variable Removed	Number Vars In	Partial R-Square	Model R-Square	C(p)	F Value	Pr > F
1	BRTE_Hydro_Good		1	0.2317	0.2317	9.9366	18.40	<.0001
2	ELEL_Hydro_Good		2	0.0776	0.3093	4.9720	6.74	0.0118
3	FEID_Hydro_Good		3	0.0376	0.3470	3.5943	3.40	0.0702

14:00 Wednesday, June 24, 2015

The REG Procedure
Model: MODEL1
Dependent Variable: Perrenial_Cover

Number of Observations Read 63
Number of Observations Used 63

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	3	1661.59810	553.86603	10.45	<.0001
Error	59	3127.07925	53.00134		
Corrected Total	62	4788.67736			

Root MSE	7.28020	R-Square	0.3470
Dependent Mean	18.71556	Adj R-Sq	0.3138
Coeff Var	38.89920		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|

Intercept	1	55.21600	13.23199	4.17	0.0001
ELEL_Hydro_Good	1	303.71566	153.06491	1.98	0.0519
BRTE_Hydro_Good	1	-434.72599	93.03362	-4.67	<.0001
FEID_Hydro_Good	1	646.17085	350.37872	1.84	0.0702

Table 9: Full Stepwise regression Results for Comparison between Perennial and Annual Cover to RSI Annual, and Seasonal Good Bad and Average Categories

Figures

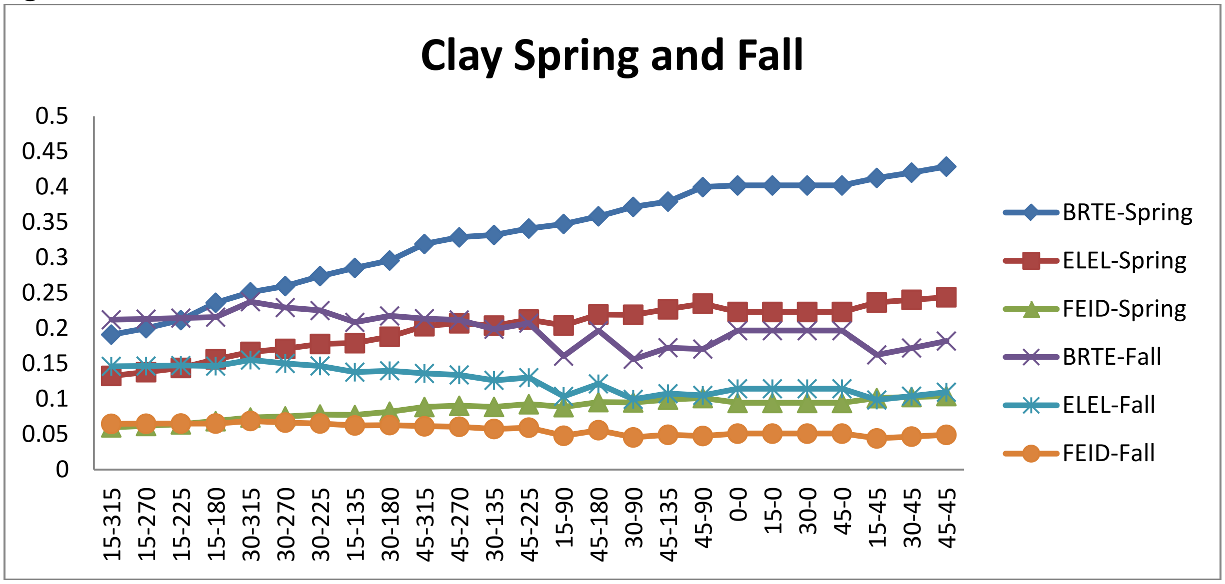


Figure 8: Comparison of Rate Sum Index (RSI) between Spring and Fall Periods of growth in Clay Soil. Slope and Aspect categories on the X axis and RSI is on the Y axis.

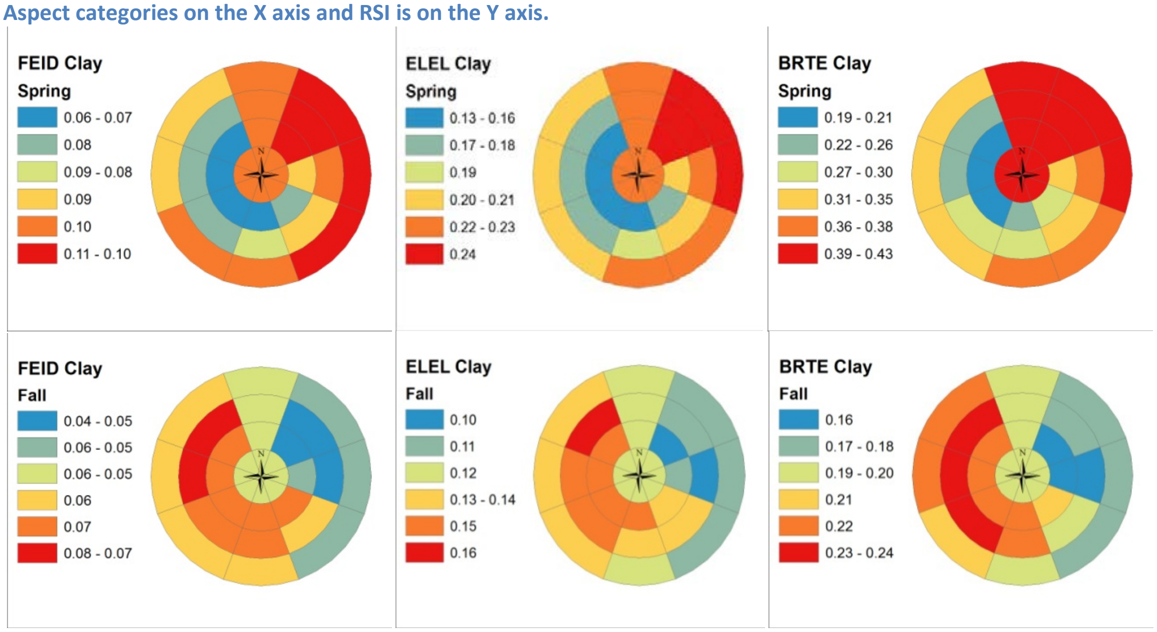


Figure 9: Topographic distribution of Clay RSI with increasing Slope from inner to outer rings.

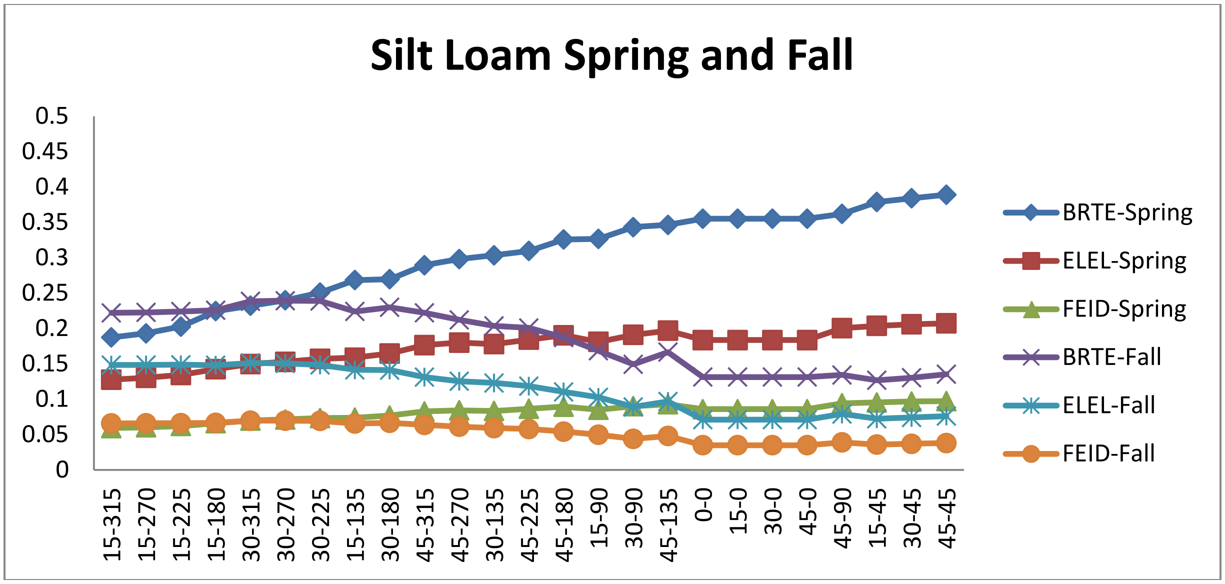


Figure 10: Comparison of Rate Sum Index (RSI) between Spring and Fall periods of growth in Silt Loam. Slope and Aspect categories on the X axis and RSI is on the Y axis.

Figure 11: Topographic distribution of Silt-Loam RSI with increasing Slope from inner to outer rings.

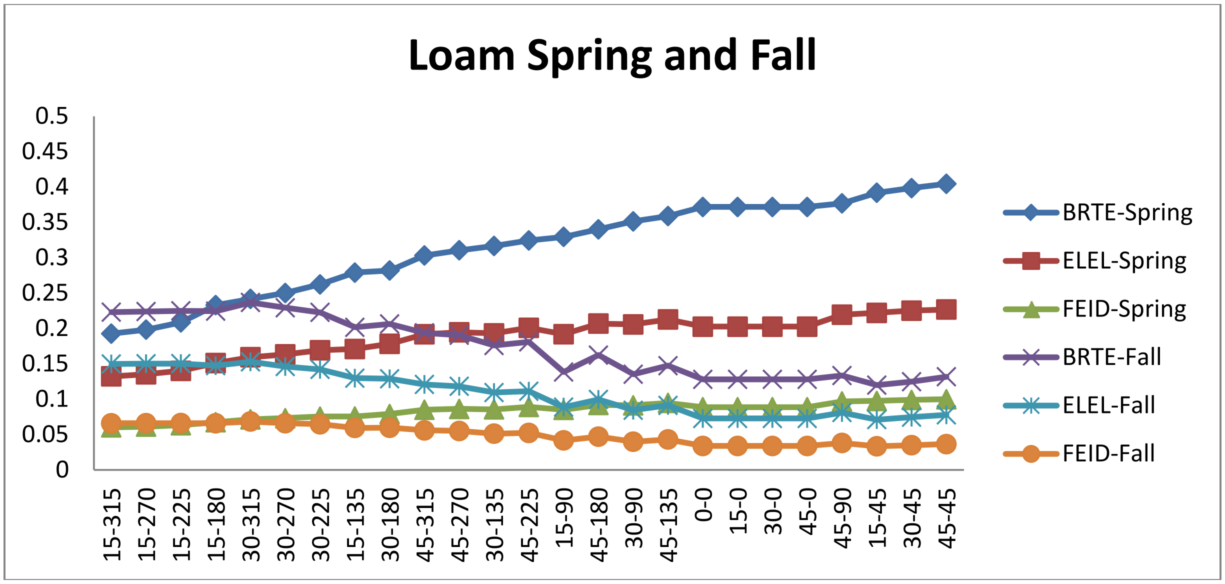


Figure 12: Comparison of Rate Sum Index (RSI) between Spring and Fall periods of growth in Loam. Slope and Aspect categories on the X axis and RSI is on the Y axis.

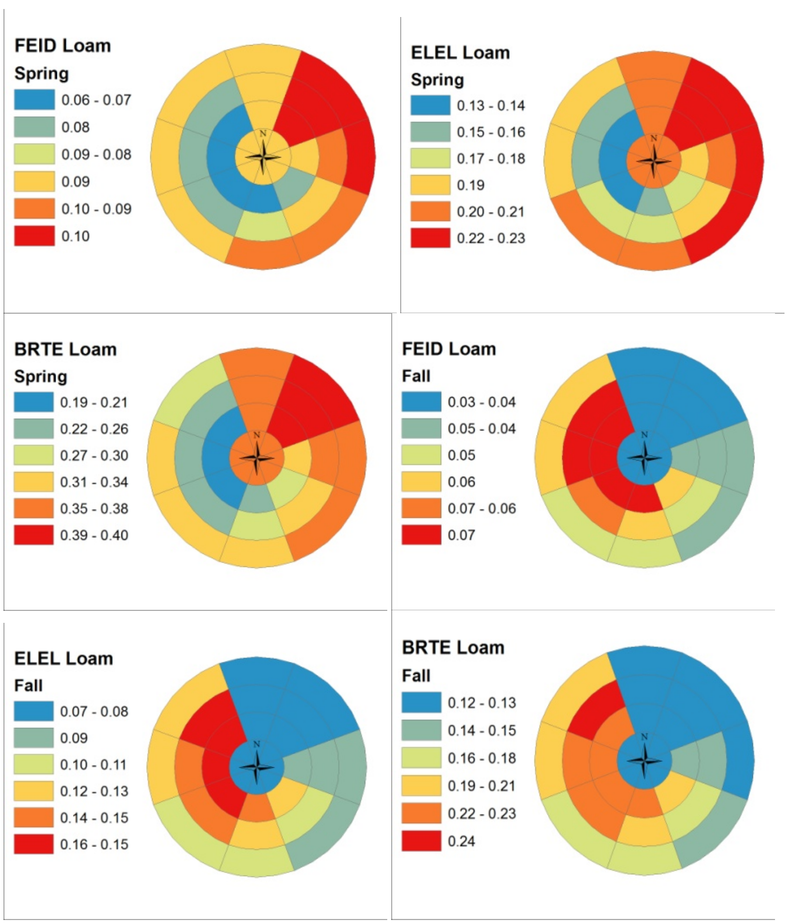


Figure 13: Topographic distribution of Loam RSI with increasing Slope from inner to outer rings.

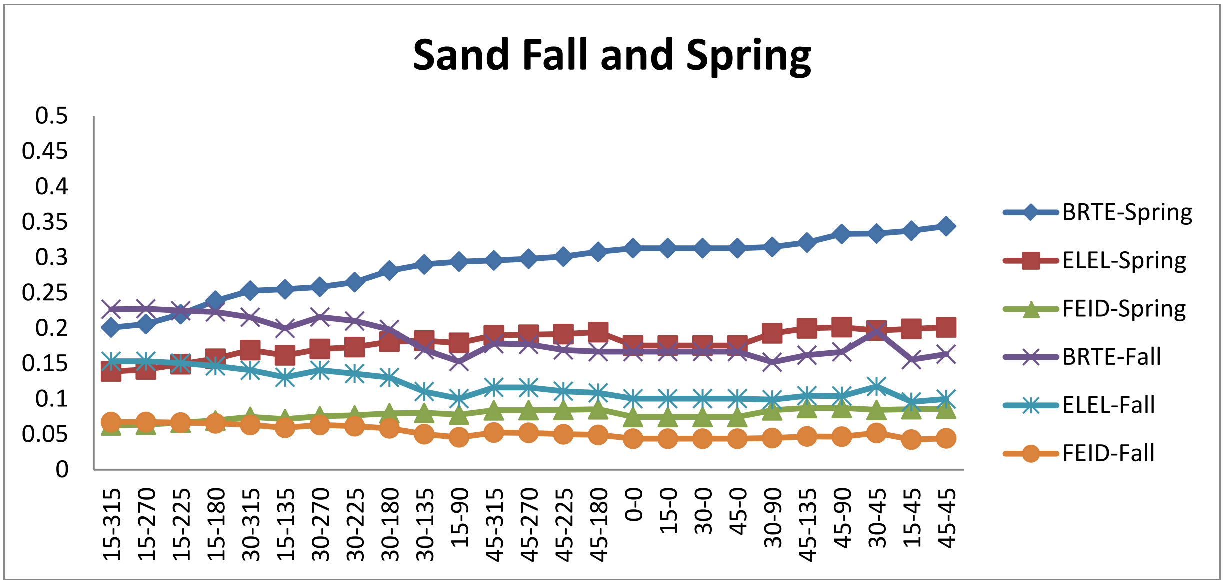


Figure 14: Comparison of Rate Sum Index (RSI) between Spring and Fall periods of growth in Sand.

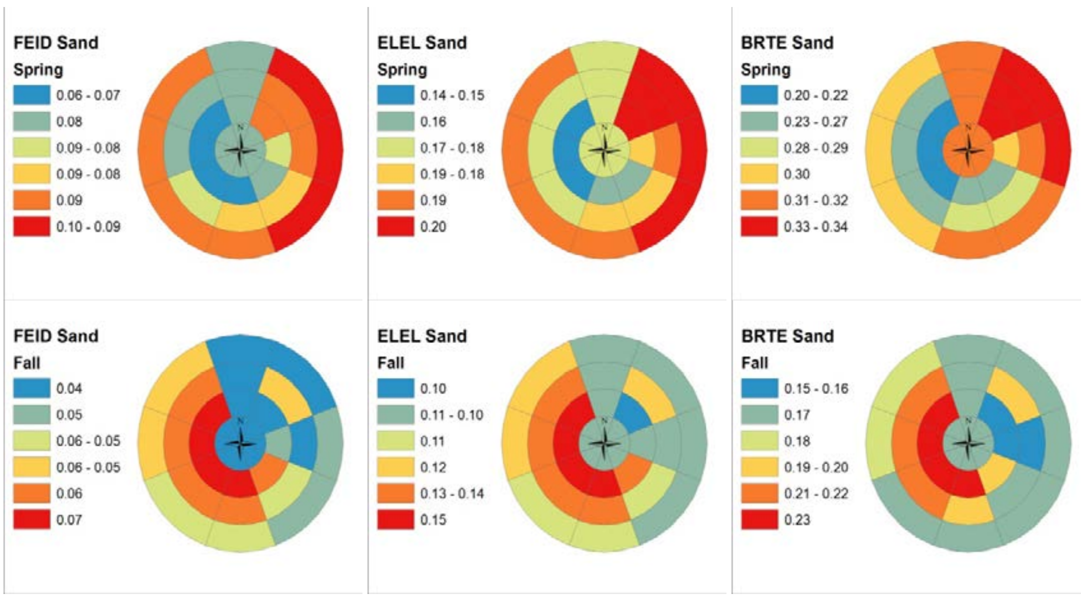


Figure 15: Topographic distribution of Sand RSI with increasing Slope from inner to outer rings. Slope and Aspect categories on the X axis and RSI is on the Y axis.

Appendix B: RSI Model Steps

RSI model Step by Step Guide

The Steps presented here are designed to allow a user to create the reference and initial condition data for running a combined Simultaneous Heat and Water (SHAW) model in conjunction with a Seedling Germination Model to produce a monthly average germination rate for a given watershed based on the physical soil characteristics, topography and climate. The end result will be a Species specific Rate Sum Index that can be used as a Bio Assay for quantifying soil specific resilience for each polygon within the area of interest.

The Steps in this document will include:

1. Soil information acquisition
2. Climate Data acquisition
3. Combining the information in a spatial environment using ARCMAP
4. Using the combined tables generated by ARCMAP in SAS to generate bulk file runs
5. Using the outputted Germination information in ARCMAP

Requirements to assemble and run this model

1. Access to the Internet
2. A GIS platform such as ARCMAP
3. SAS

Input tables and Source Data

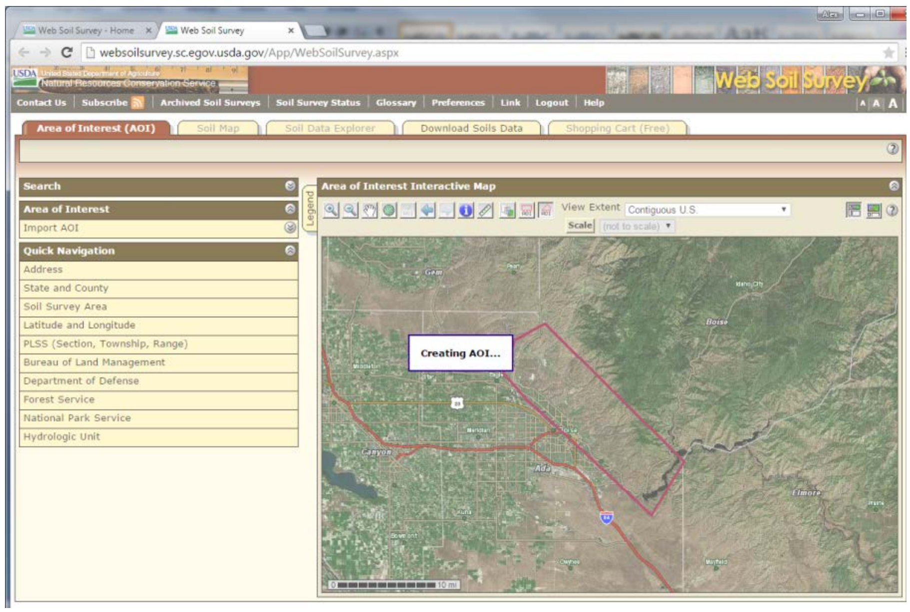
Step 1: Obtaining input data

Web Soil survey can provide the data for a geospatial processing step for extracting the required physical properties of a soil polygon. The tool can also provide a pdf report of the area you are interested in which has derived values from the soil survey. Additional information includes Ecological Site Descriptions and some back ground information regarding parent materials.

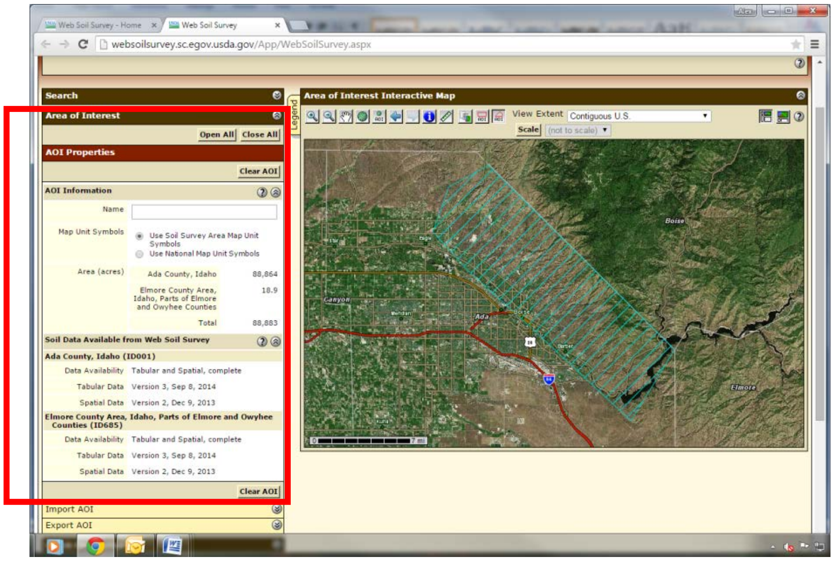
Obtaining Tabular and Spatial information from Web Soil Survey

- Go to Web Soil Survey hosted by USDA NRCS at: http://websoilsurvey.sc.egov.usda.gov/App/HomePage.htm
- Select the big Green Button: “Start WSS”

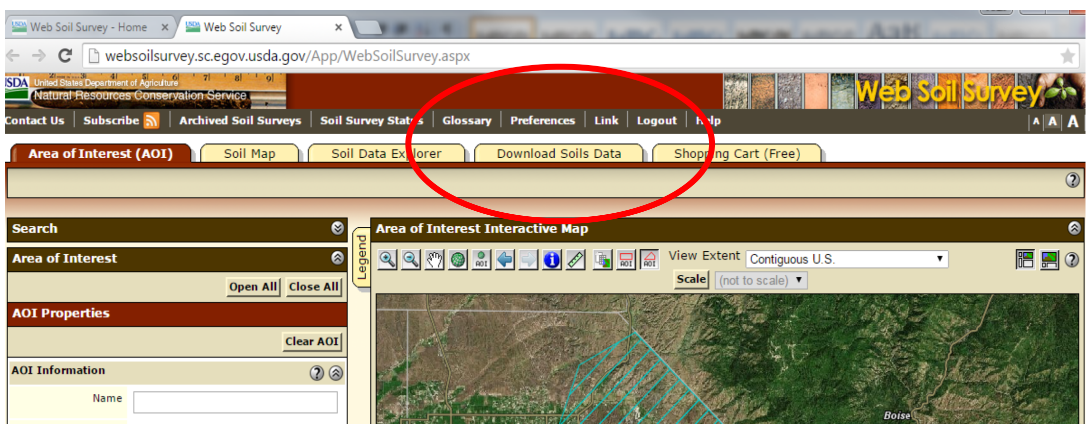
- Zoom in to Area of Interest using Map interface tools and mark out the Area of Interest (AOI) you need soils information from.



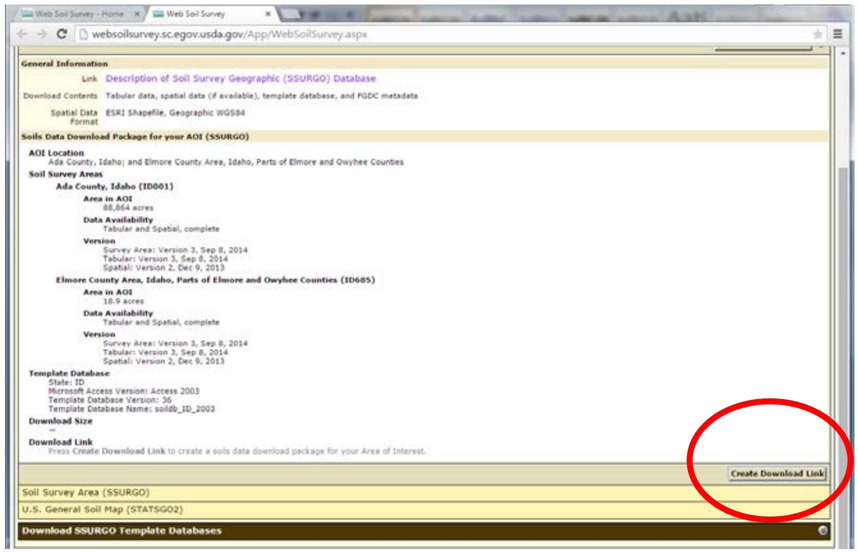
- If you select areas outside of one county you will receive a message indicating "Multiple Soil Survey Areas in your Area of Interest". This matters when you need to put your tabular data together where the two counties might be using different codes for linking the tables together. Due to constraints from how the SSURGO databases are developed it is highly inadvisable to import areas that include other counties at this. Later versions may have fixed this but at the time of this documentation the databases do not line up for all counties.



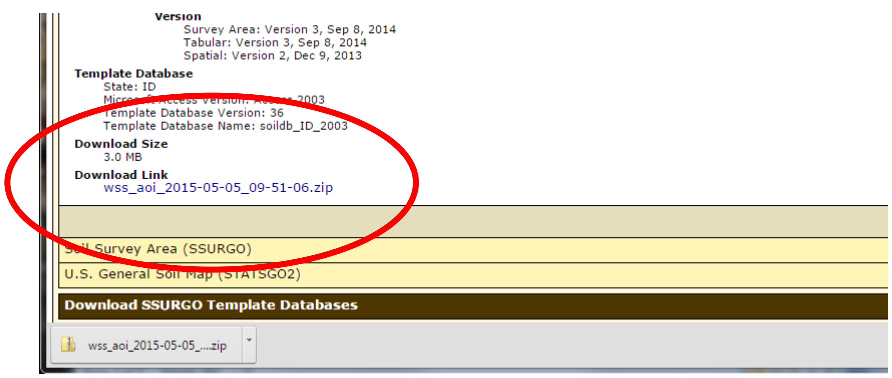
- You can extract the AOI if you need to at any step along this but you will also have it when you download the spatial and tabular databases by selecting “Download Soils Data”.



- Once you had determined your AOI and are at the download soils data, select “ Create Download Line” and wait a moment for a link to be created.



- o After some processing time a link will appear at the bottom left of your screen. Select that and go to your download folder.



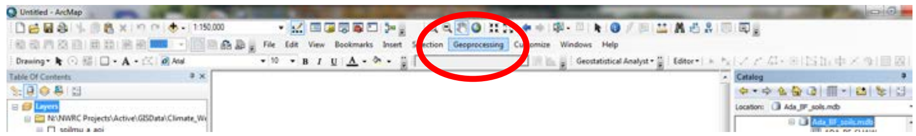
- o This automatically downloads to your download folder in windows where you can archive one copy and place and active version in your project folder where you will access it for geo-processing.

Other options for extracting information from WSS are available but those are beyond the scope of this Appendix.

Step 2 ARCMAP Assembling the tabular data

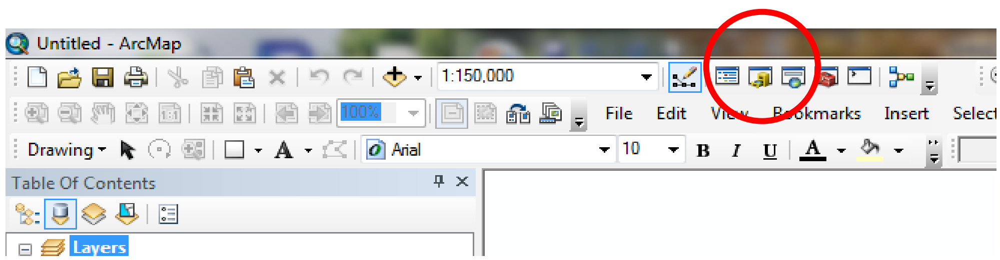
The objective of this step will be to load the SSURGO data into ARCMAP, set up a geodatabase, and link the necessary fields together containing soil texture and bulk density information. SSURGO is a Relatable Database Management System (RDBMS) and assuming all the tables are in a current version can be joined together using the Join Feature in Arcmap to generate an attribute table with all the necessary information in for SHMODEL. By the end of this step you will have a csv table that can be read by SAS which will then create the input tables for running SHMODEL (Mostly Just SHAW at this stage)

- Open an ARCMAP Document (*.mxd) and set up your Environments for the folder you are working in.



- SSURGO comes with a defulat DATUM so if you need the information in a specific format change it now.

- If not activated select ArcCatalog in the side panel and Navigate to your project folder.



- Load the spatial data from your geodatabase and the following tables
    1. Mapunit
    2. Component
    3. Chorizon
    4. Chtexturegrp
    5. Chtexture
    6. Shape file with the soil polygons in the SSURGO database

- The Joins between tables should go as follows:
    1. MUKEY in mapunit to MUKEY in the component table
    2. COKEY in the component table to COKEY in the chorizon table
    3. CHKEY in the chorizon table to CHKEY in the chtextgrp table

4. CHTGKEY in the chtexturegrp table to CHTGKEY in the chtexture table

- Once the Joins are complete **Right Click** the target soil polygon file with all the joins on it and **Export** the shapefile to a feature class or with the tables so that the joins are permanent

- Open the new file and turn off all the superfluous fields that are not representative of the specific polygon. Each field with an “_r” or a ”rep” attached to it can be turned off, i.e. sandtotal_r is desirable and sandtotal_h or _l is not. The goal is to obtain representative values for the polygon.

Table

Export_Output

OBJECTID *	slope_r	elev_r	aspectrep	taxclname	sandtotal_r	silttotal_r	claytotal_r	om_r	dbovendry_r
1	35	978	180	Clayey, smectitic, mesic, sh	35	45	20	2	1.18
2	35	978	180	Fine, smectitic, mesic Leptic	24	43	33	1.5	1.43
3	35	978	180	Clayey-skeletal, smectitic, m	55	29	16	2	1.16
4	60	1341	360	Sandy-skeletal, mixed, mesi	80	18	2	0.75	1.51
5	60	1341	360	Coarse-loamy, mixed, super	60	32	8	3	1.43

- Open the Attribute table for the New Shape file with the soil polygons and the added field and Add a Field called “Linkme”. It can be a test file or a numeric.

Table

Export_Output

OBJECTID *	slope_r	elev_r	aspectrep	taxclname	sandtotal_r	silttotal_r	claytotal_r	om_r	dbovendry_r	LinkMe
1	35	978	180	Clayey, smectitic, mesic, sh	35	45	20	2	1.18	1
2	35	978	180	Fine, smectitic, mesic Leptic	24	43	33	1.5	1.43	2
3	35	978	180	Clayey-skeletal, smectitic, m	55	29	16	2	1.16	3
4	60	1341	360	Sandy-skeletal, mixed, mesi	80	18	2	0.75	1.51	4
5	60	1341	360	Coarse-loamy, mixed, super	60	32	8	3	1.43	5
6	60	1341	360	Sandy-skeletal, mixed, mesi	70	24	6	3	1.42	6

0 (0 out of *2000 Selected)

- Highlight the LinkMe field and select “Field Calculator”. Use the ObjectID field as a reference and select ok. This field will be used later to link to the rest of the variables.

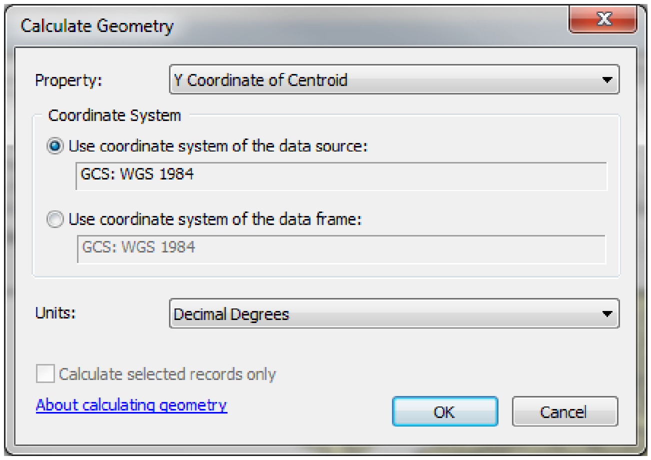
Table

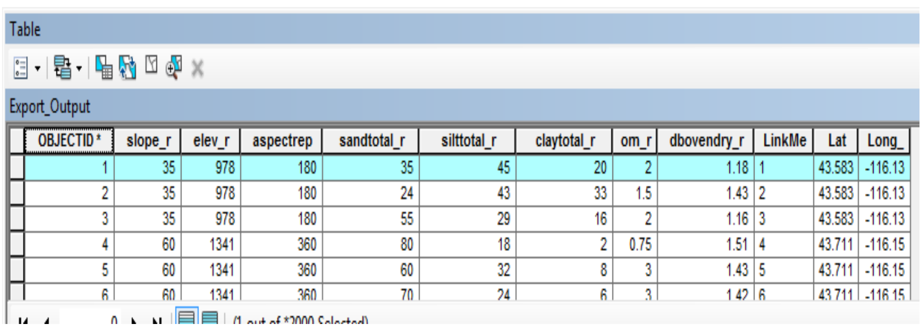
Export_Output

OBJECTID *	slope_r	elev_r	aspectrep	taxclname	sandtotal_r	silttotal_r	claytotal_r	om_r	dbovendry_r	LinkMe
1	35	978	180	Clayey, smectitic, mesic, sh	35	45	20	2	1.18	1
2	35	978	180	Fine, smectitic, mesic Leptic	24	43	33	1.5	1.43	2
3	35	978	180	Clayey-skeletal, smectitic, m	55	29	16	2	1.16	3
4	60	1341	360	Sandy-skeletal, mixed, mesi	80	18	2	0.75	1.51	4
5	60	1341	360	Coarse-loamy, mixed, super	60	32	8	3	1.43	5
6	60	1341	360	Sandy-skeletal, mixed, mesi	70	24	6	3	1.42	6

0 (0 out of *2000 Selected)

o Add two more fields for Latitude (Y) and Longitude (X). Type should be Double. Right Click on each field and select "Calculate Geometry". This step will provide an X and Y coordinate for each Polygon Centroid which will be used in SHAW. Use Decimal Degrees





Table

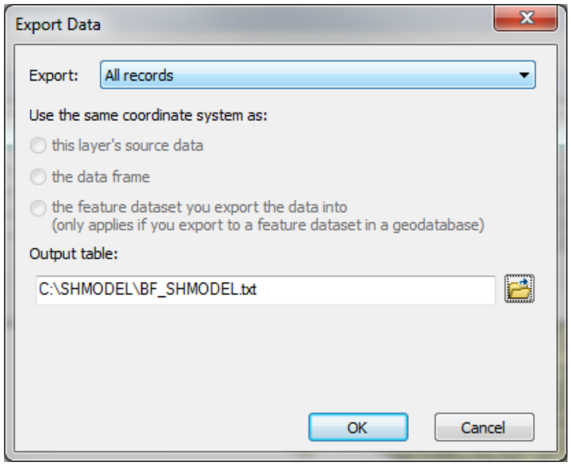
Export_Output

OBJECTID *	slope_r	elev_r	aspectrep	sandtotal_r	silttotal_r	claytotal_r	om_r	dbovendry_r	LinkMe	Lat	Long_
1	35	978	180	35	45	20	2	1.18	1	43.583	-116.13
2	35	978	180	24	43	33	1.5	1.43	2	43.583	-116.13
3	35	978	180	55	29	16	2	1.16	3	43.583	-116.13
4	60	1341	360	80	18	2	0.75	1.51	4	43.711	-116.15
5	60	1341	360	60	32	8	3	1.43	5	43.711	-116.15
6	60	1341	360	70	24	6	3	1.42	6	43.711	-116.15

(1 out of *2000 Selected)

Once complete with this step you should have the above fields in your attribute table.

o From this table select export data. Doing so from the Attribute table allows you to export the table and not the spatial components which you don't need for the rest of the modeling until you link the data back in for further geoprocessing. Export to a directory from which you will be running SHMODEL and save as a **Text File.**



Climate File Extraction and Formatting:

The objective of this step is to assemble a climate file that can be read by SHAW that is formatted correctly so as not to break SHAW. Daily Climate data can come from a number of sources such as MesoWest, NOAA, or gridded weather data obtained from either METDATA hosted by the University of Idaho (http://metdata.northwestknowledge.net/)or from Daymet hosted by Oakridge National Laboratory (http://daymet.ornl.gov/). METDATA is the most complete though it has some limitations in regards to spatial distribution being 4 km and the data being completely in Netcdf.

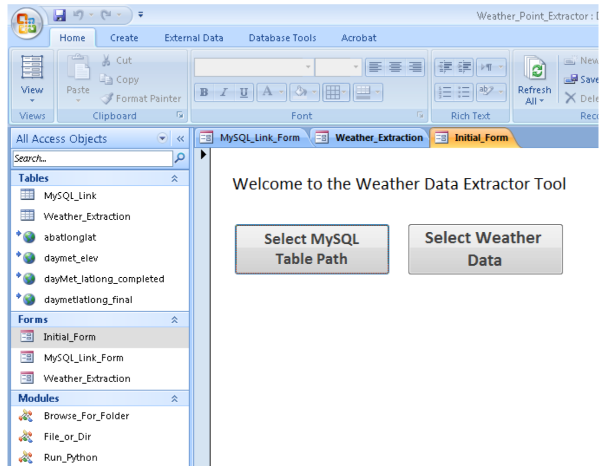
You will need on your machine:

1. MySQL workbench 6.0 CE
2. Microsoft Access vs 2007 or newer
3. Python 26 and Python 27
4. ARCMAP 10.1 or newer
5. MS Access tool downloaded from this FTP site hosted by the Northwest Watershed Research Center: ftp://ftp.nwrc.ars.usda.gov/public/UofIMetData/
6. The specific gridded data required for you study Area. You can follow SOP's provided by Daymet and METDATA to obtain that information. These data can be substantial so you might want to explore external storage options.

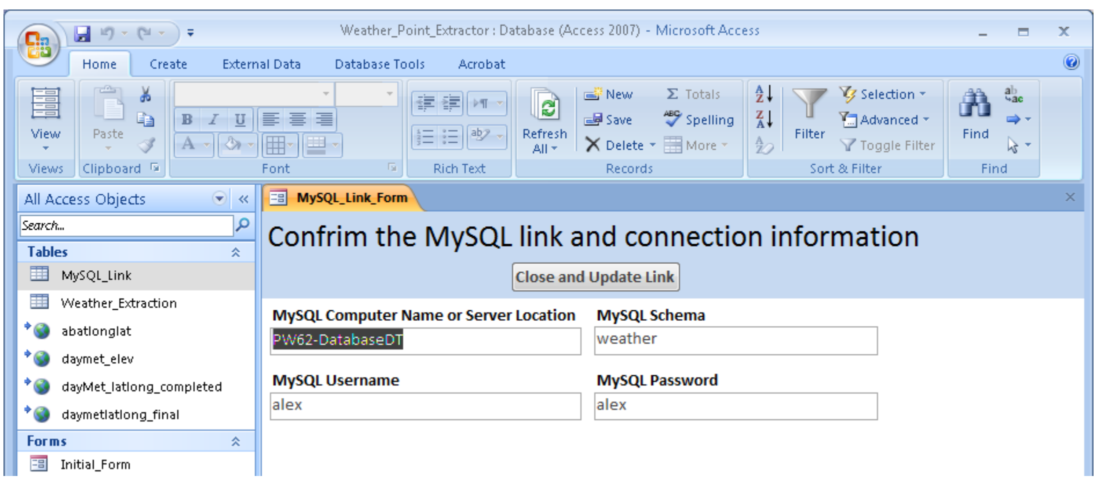
Additional steps for preparing to use this tool. Access needs to have the ODBC directories

Load these afformentioned programs and data libraries allong with suplimentary packages from the FTP site linked above.

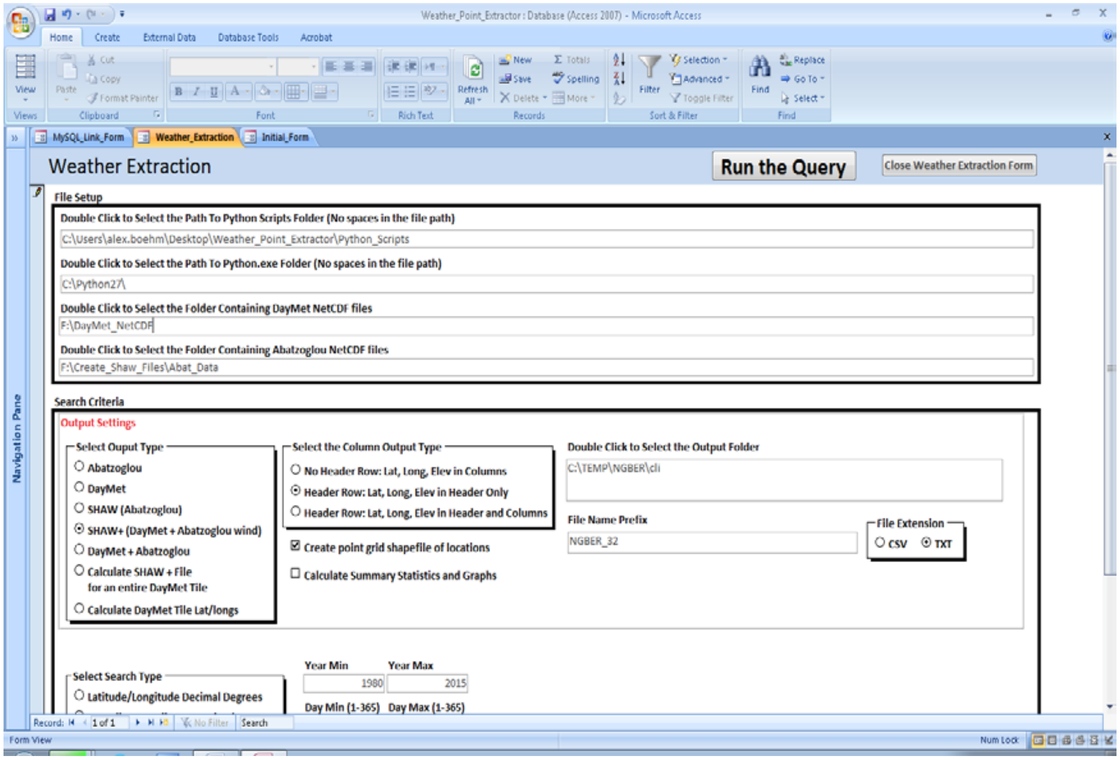
Open the MS Access tool: Weather_Point_Extractor.accd and “Enable the Content”



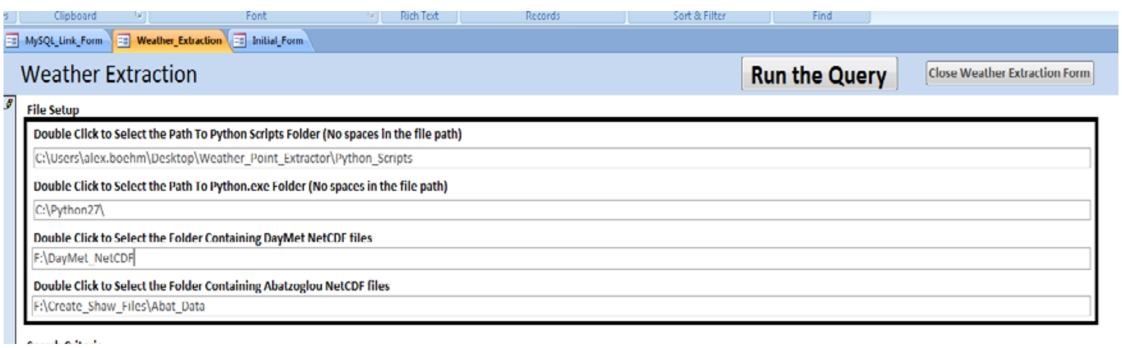
From the Initial Form select the “Select MySQL Table Path” Button and define the parameters below:



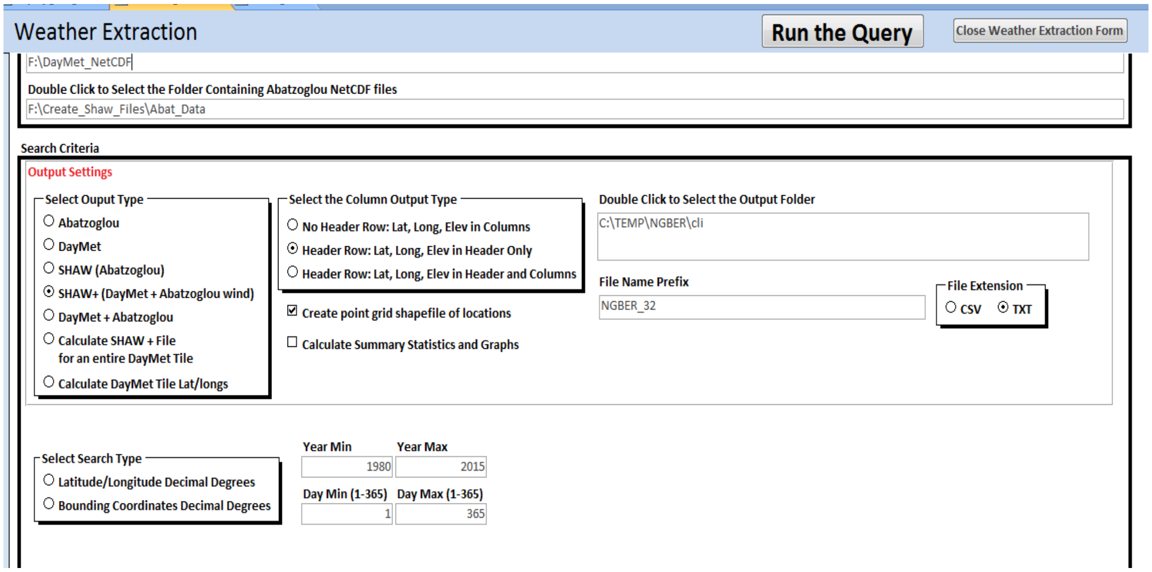
Once selected go to the **Initial Form** and choose “Select Weather Data”



From this form you will need to link to your METDATA information and your Daymet infromation under **File Setup**.



Next go to **Search Criteria**



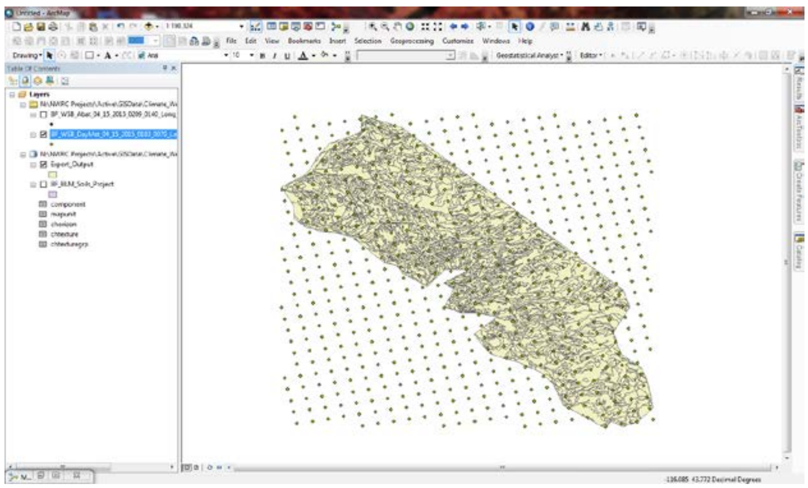
- At this point you will select the file output type you need, in this Case SHAW+(Daymet + Abatzoglou Wind). If this is the first time running this tool an upfront steps required for this procedure include processing the X and Y locations for each point in the gridded data sets within each tile. This will take some time depending on your processer.
- Once you have selected the output type select the column output type.
- Select the option for “Create point grid shapefile of locations”. This is critical for linking back to the reference table being read by SAS (See Arcmap Steps).
- Determine the Output folder and provide a prefix for the files your are creating
- Select file extension, (SHAW works best with .csv)
- If you are doing one location or a region you may run into a message that says it needs to calculate the coordinates for the grid. This will take some time but further operations will go much faster.

Once you are complete and have your climate files each header should appear as below and explicitly in this order: **Calendar Year, Calendar Month, Day, Hydrolic_Year, Hydrolic_Month, Julian_Day, Precipitation (inches), Dew_Point (%), Solar_Radiation (W/m^2), Max_Temperature (C), Min_Temperature (C), Wind Speed (mph)**. SHAW will ignore any additional information but I fyou are assembling a climate file independently of this tool using other resources this is the format and order the data needs to be in.

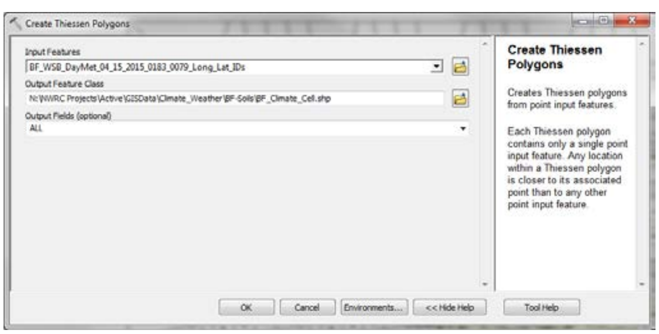
*Potential Errors with Climate data includes gaps, 0 values and out of range values such as 9999.

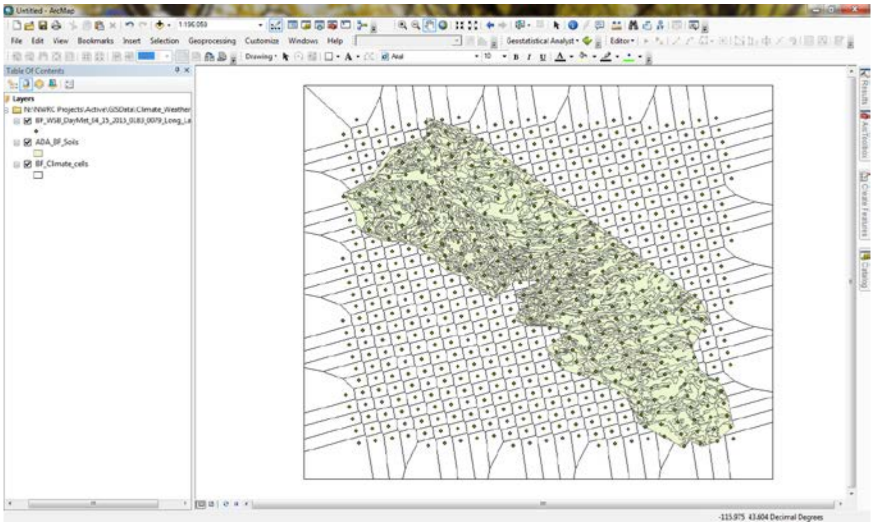
Merging the Climate, Soils and Topographic Data together to build a reference look-up table for SHMODEL

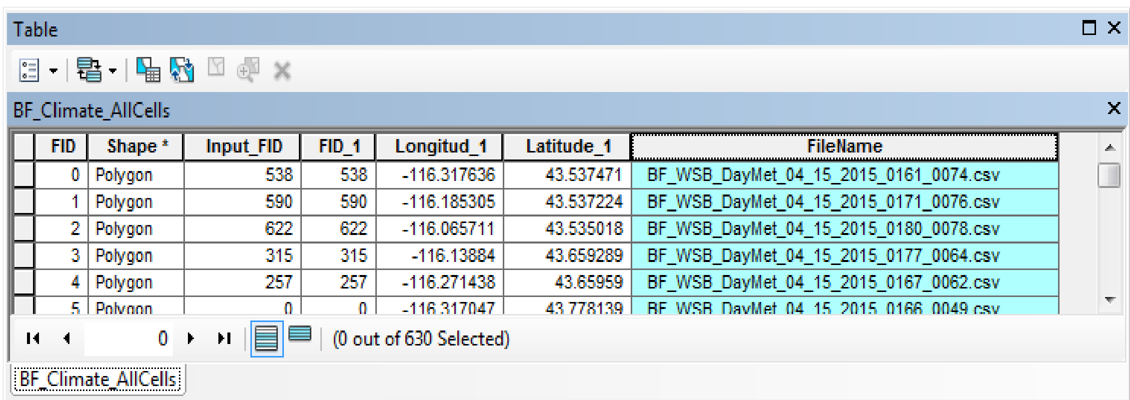
In ARCMAP load the outputted Daymet points extracted by the Weather Point Extractor Tool and the Soil Polygon Data extracted using Web Soil Survey with the associated texture and bulk density data.



You will create a Theissen Pylogon around each point which will be used in the merging process with some of the other input information. Ensure you include all the attribute fields from the input data into the output data. The objective of this step is to end up with a representative polygon with the associated Climate file name that can be referenced in a look up table.







Table

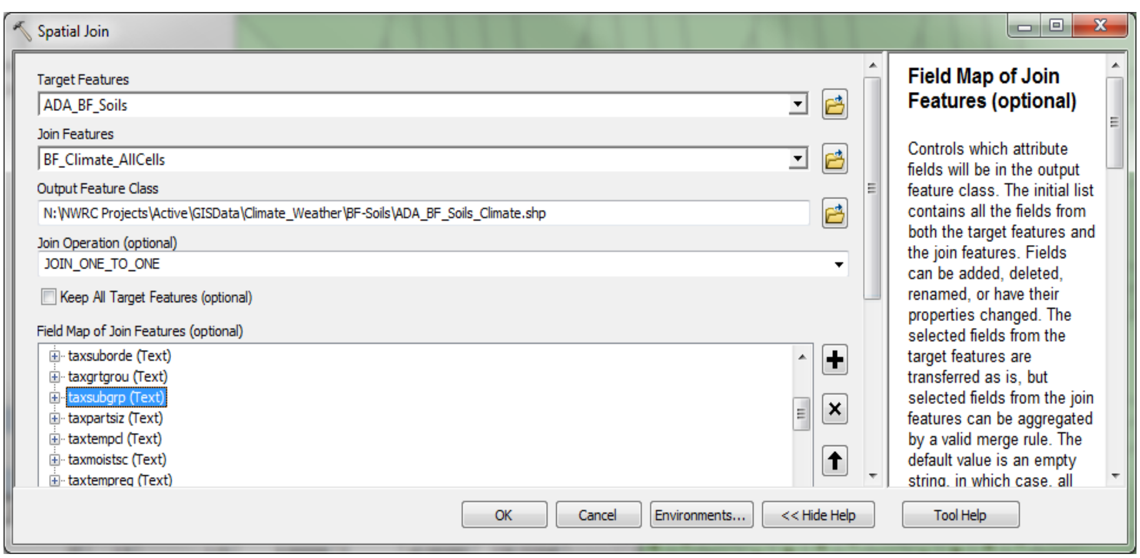
BF_Climate_AllCells

FID	Shape *	Input_FID	FID_1	Longitud_1	Latitude_1	FileName
0	Polygon	538	538	-116.317636	43.537471	BF_WSB_DayMet_04_15_2015_0161_0074.csv
1	Polygon	590	590	-116.185305	43.537224	BF_WSB_DayMet_04_15_2015_0171_0076.csv
2	Polygon	622	622	-116.065711	43.535018	BF_WSB_DayMet_04_15_2015_0180_0078.csv
3	Polygon	315	315	-116.13884	43.659289	BF_WSB_DayMet_04_15_2015_0177_0064.csv
4	Polygon	257	257	-116.271438	43.65959	BF_WSB_DayMet_04_15_2015_0167_0062.csv
5	Polygon	0	0	-116.317047	43.778139	BF_WSB_DayMet_04_15_2015_0166_0049.csv

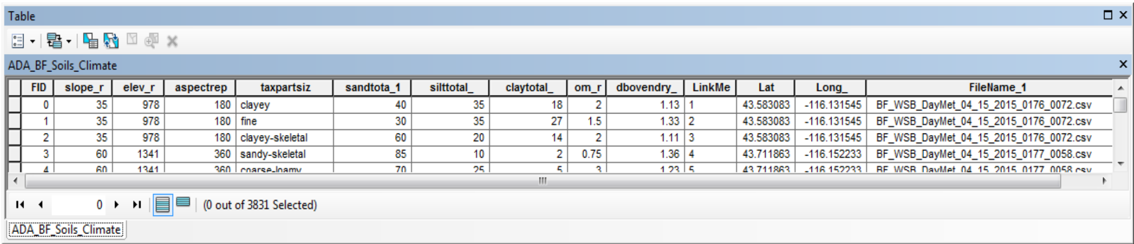
(0 out of 630 Selected)

BF_Climate_AllCells

Once this step is complete you will do a Spatial Join to merge the needed fields together for creating the final look-up table for SHMODELing. The Target Feature should be the soils file and the Join Feature should be the Climate file. The Join should be One to One since the One To Many option creates extra rows of data that only contribute superfluous work for later.



At the end of the Join process you will end up with an Attribute table with soil texture, bulk density, texture, topography and related climate file.



FID	slope_r	elev_r	aspectrep	taxpartsiz	sandtota_1	silttotal_	claytotal_	om_r	dbovendry_	LinkMe	Lat	Long_	FileName_1
0	35	978	180	clayey	40	35	18	2	1.13	1	43.583083	-116.131545	BF_WSB_DayMet_04_15_2015_0176_0072.csv
1	35	978	180	fine	30	35	27	1.5	1.33	2	43.583083	-116.131545	BF_WSB_DayMet_04_15_2015_0176_0072.csv
2	35	978	180	clayey-skeletal	60	20	14	2	1.11	3	43.583083	-116.131545	BF_WSB_DayMet_04_15_2015_0176_0072.csv
3	60	1341	360	sandy-skeletal	85	10	2	0.75	1.36	4	43.711863	-116.152233	BF_WSB_DayMet_04_15_2015_0177_0058.csv
4	60	1341	360	coarse-loamy	70	25	5	3	1.23	5	43.711863	-116.152233	BF_WSB_DayMet_04_15_2015_0177_0058.csv

If necessary a follow up step will be to incorporate as detailed a terrain model as possible you will then perform a raster math application using the 10m DEM. Soil Survey provide a reference value for slope, aspect and elevation but is derived using a 30m DEM. A 10m DEM will provide potentially more detailed topographic values then the 30m DEM.

An Alternative procedure for bring all the necessary elements together for the creating and input SHMODEL table will be to us ArcMap Model Builder. The required inputs for this procedure include:

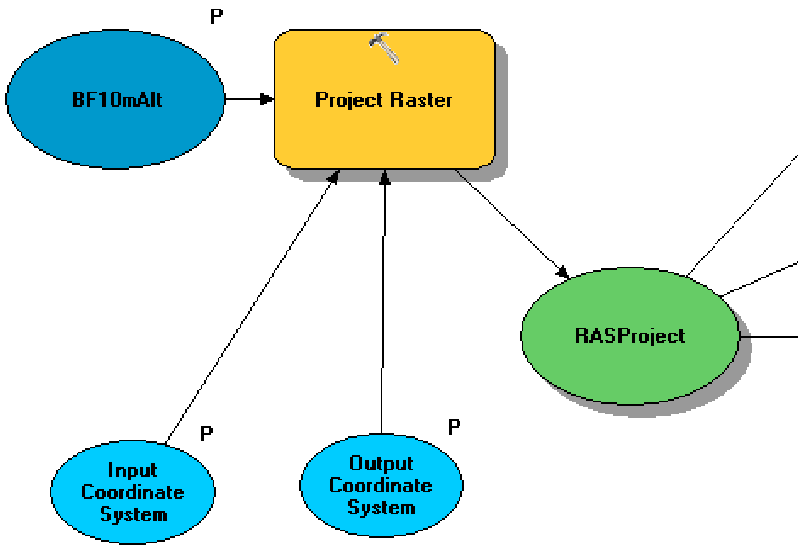
1. **Soils Polygon Data Acquired from Web Soil Survey SSURGO data base**
2. **10m Digital Elevation Model (DEM)**
3. **Reference Climate data Acquired from a Gridded Climate data set.**

A step by step method is presented here using ArcGIS Model builder:

It is advisable to set all the outputs to the same database as well as setting the Environmental settings to this same location. The steps will be outlined beginning from DEM and shapefile organization adding the fields, zonal statistics and joining the results.

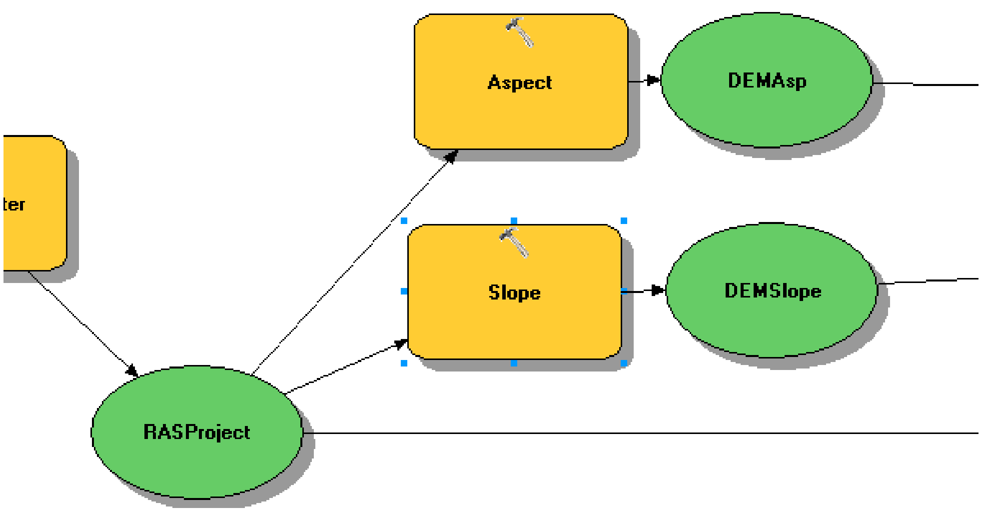
Step 1: Input Raster Projection

The first step is to ensure both the input DEM and Soil shape file are in the same projection.



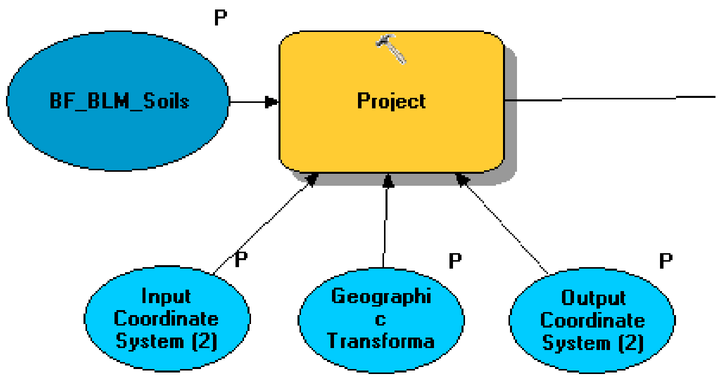
Step 2:

From the newly projected raster calculate **Slope** and **Aspect**. For both tools use the default settings. Elevation data doesn't require any further calculation from the DEM.



Step 3: Take a pause from the raster and start preparing the soils Polygon

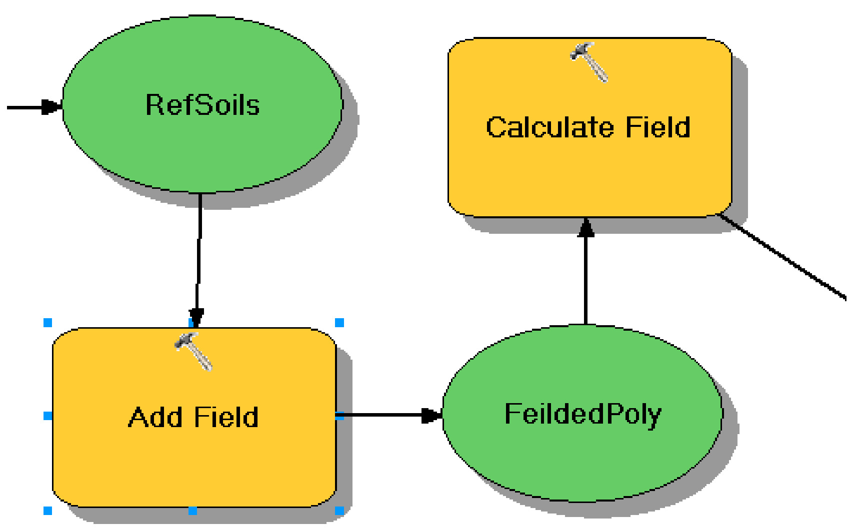
Just as with the raster preparation set up the soils shapefile by setting it to the same projection.



Step 4 and 5: Creating a common reference field for the Joins.

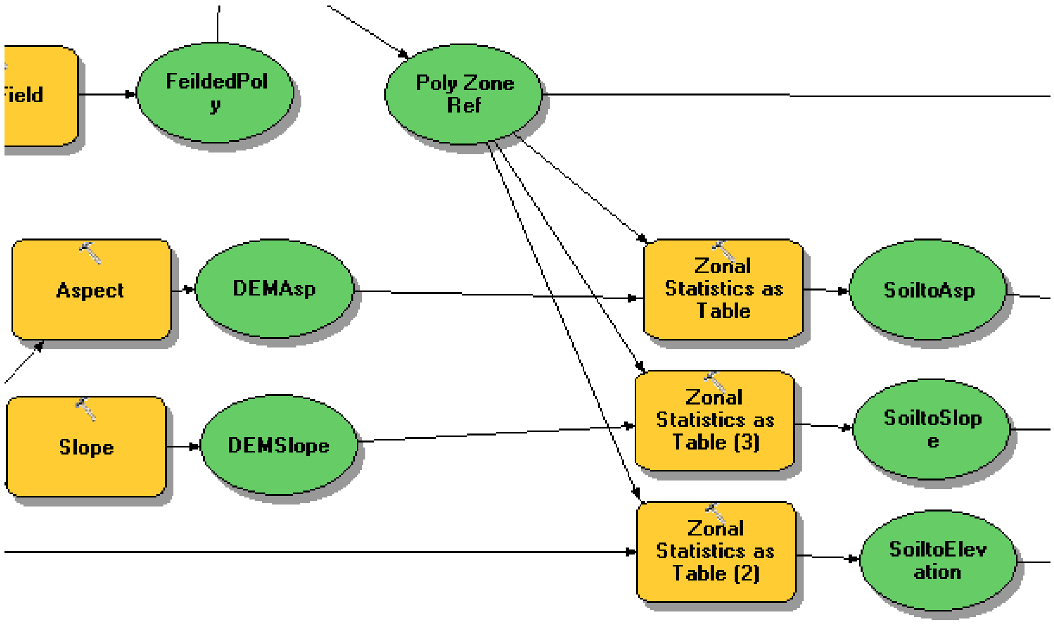
The next two steps are intended to establish the field that will be used to link the tables together. Take the newly projected soil polygon as the input table, create a unique name usable throughout this process for combining the tables (LinkMe) and field type can be a **Short** integer type.

Once a field is set up the next step is to calculate the values for it. Calculate the field as LinkMe = [Object ID].



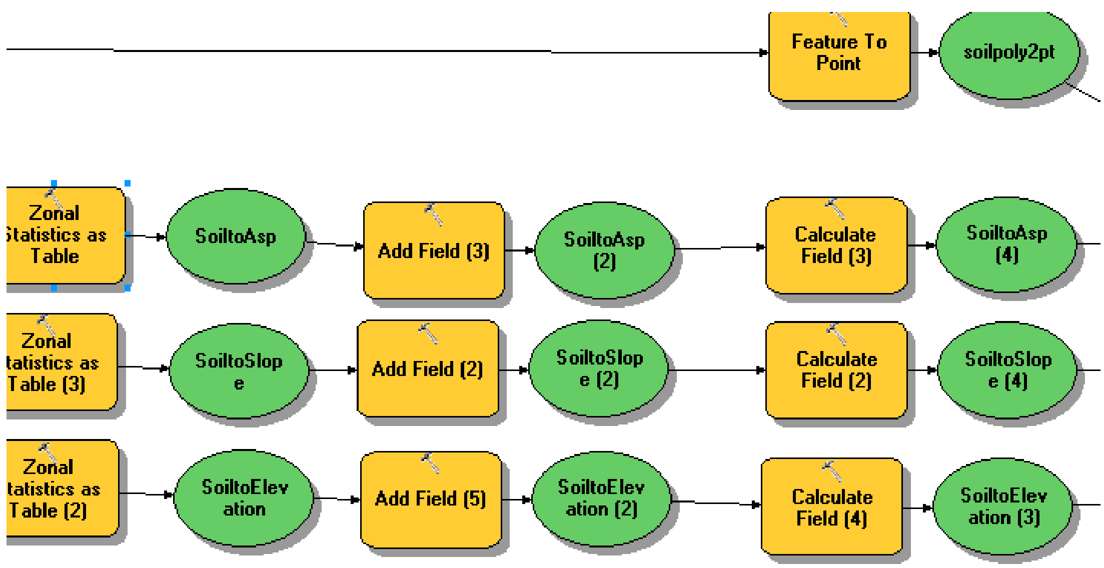
Step 6: Zonal Statistics, Calculating the values of a raster that fall within another data set.

The Raster and Reference Polygon files are now set up for Zonal Statistics. Use the reference polygon that contains the new linking field carry out zonal statistics specifying **MEAN** for each polygon field as they pertain to Slope, Elevation and Aspect. A table should be the product of this step.



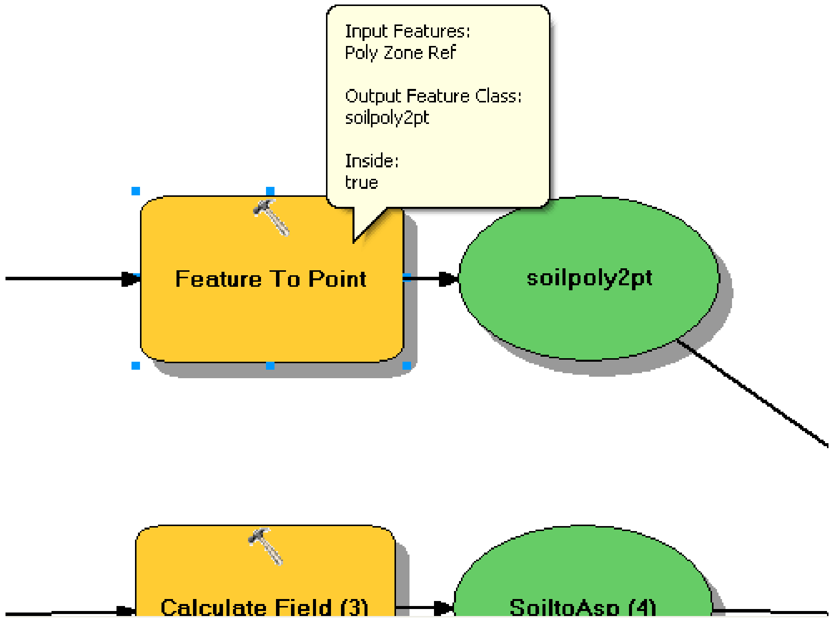
Step 7: Create Common fields for the three new tables

Calculate Fields; Select the input table for the newly created field for each raster table and calculate the MEAN. The outputted product from this step will be tables that you can then create the common fields within which should be the same as the fields created in the reference soils polygon in steps 4-5. Create a new field with the same name (LinkMe) and field type (Short) as done with the reference soil polygon.



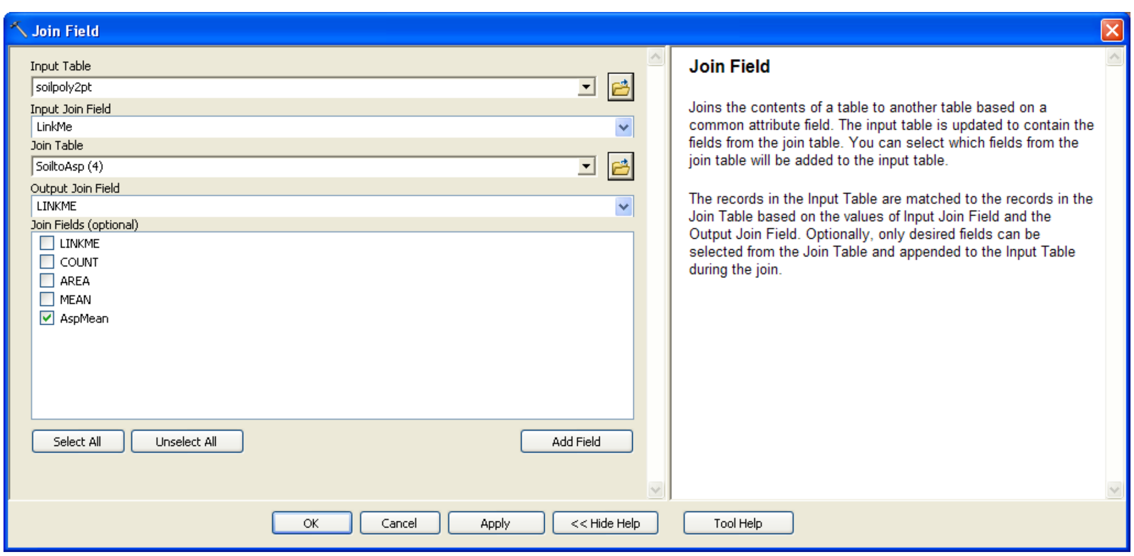
Step 8: Polygon to Point, Creating the linking shape file for all the fields

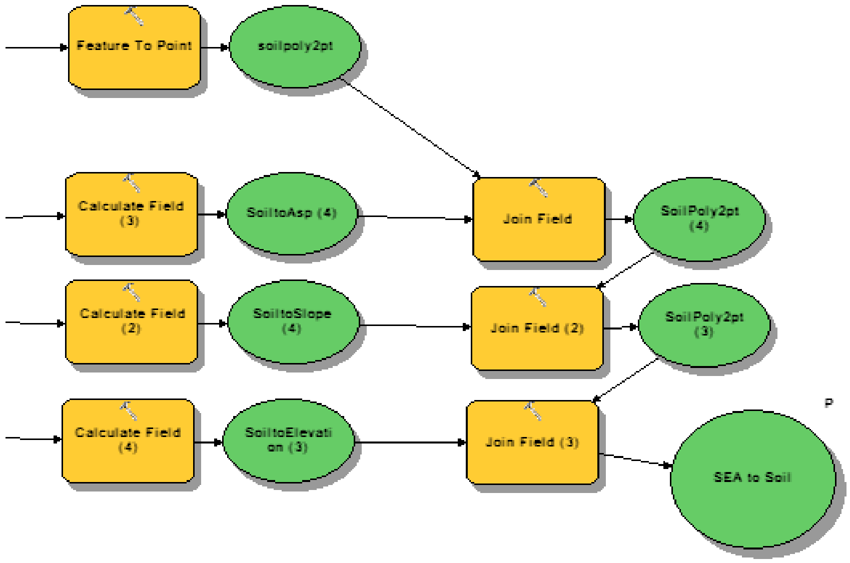
For the reference soil polygon create a point file that represents each soil polygon. The Point file will be the primary file to which the Slope, Elevation and Aspect Mean Fields will be linked. The file will be created from the reference polygon with the LinkMe field added in.



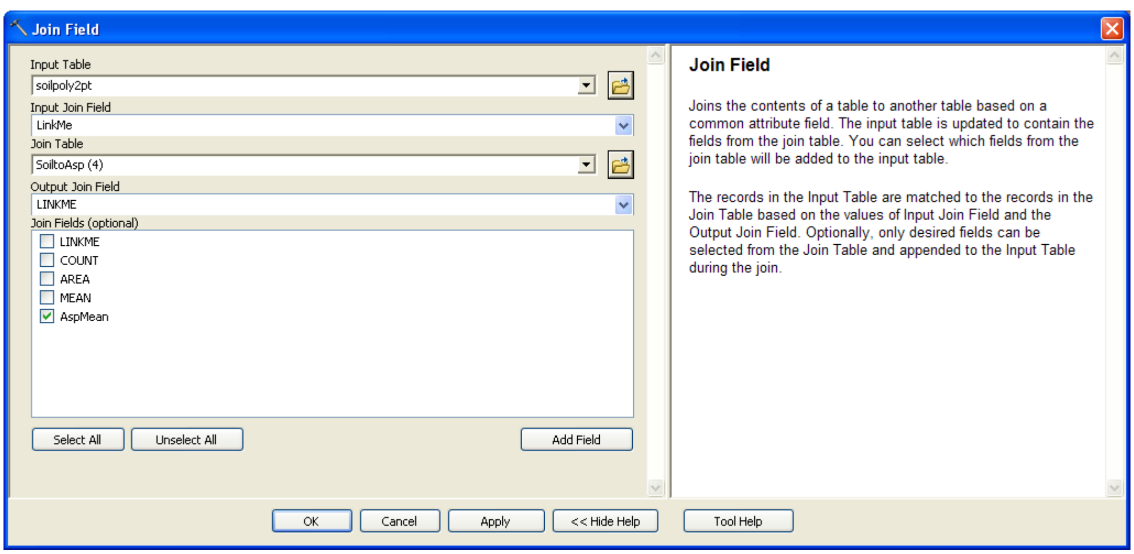
Step 9: Join One to Many

For doing a One to Many Join start with the Reference Polygon that contains the common field name (LinkMe). Input field should be LinkMe, Join table should be the first table on to link (SoiltoAsp), use common table in SoiltoAsp(4) (LinkMe) and in the join fields optional block select the Aspmean field to include in the Join. Otherwise you will end up with all the fields in all the linked tables and that is beyond what is needed and will generate superfluous data fields.



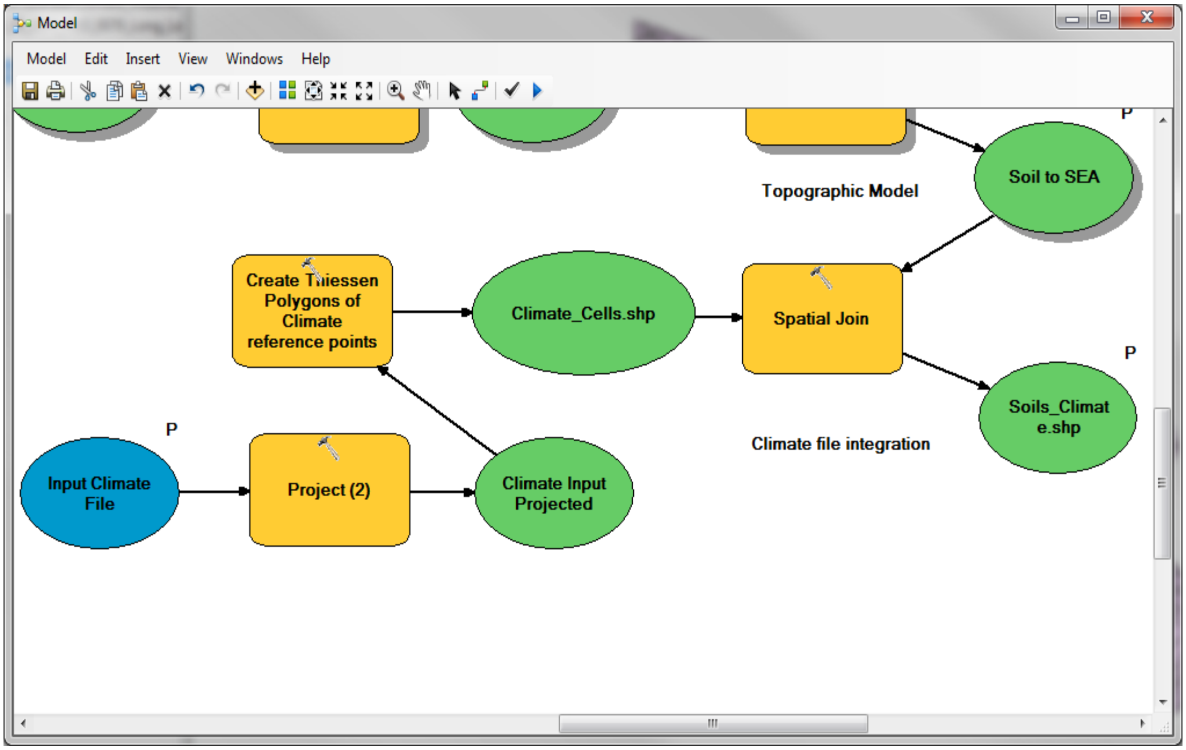


For doing a One to Many Join start with the Reference Polygon that contains the common field name (LinkMe). Input field should be LinkMe, Join table should be the first table on to link (SoiltoAsp), use common table in SoiltoAsp(4) (LinkMe) and in the join fields optional block select the Aspmean field to include in the Join. Otherwise you will end up with all the fields in all the linked tables and that is beyond what is needed and will generate superfluous data fields.



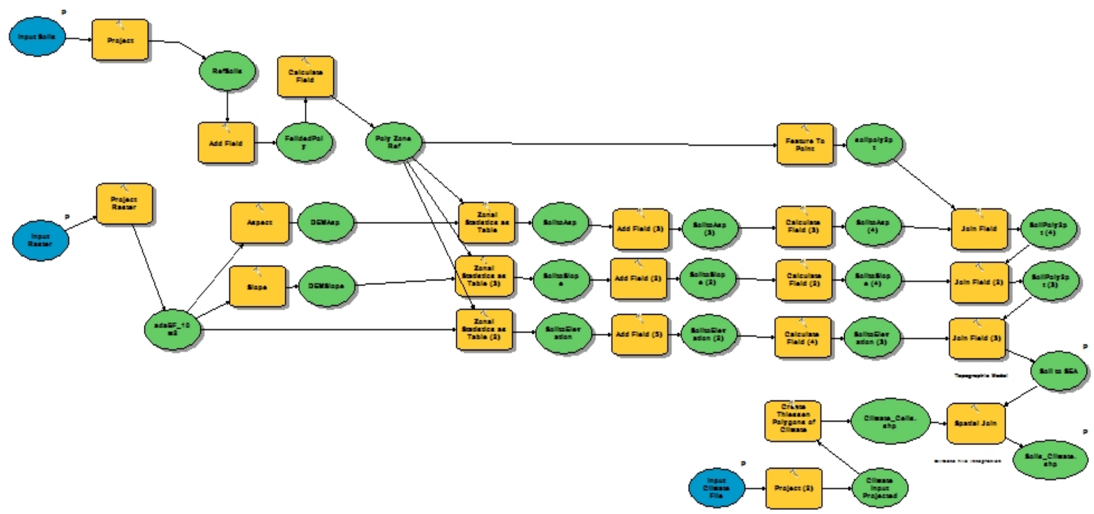
Step 10: Join One to One: Climate file to Soil2SEA

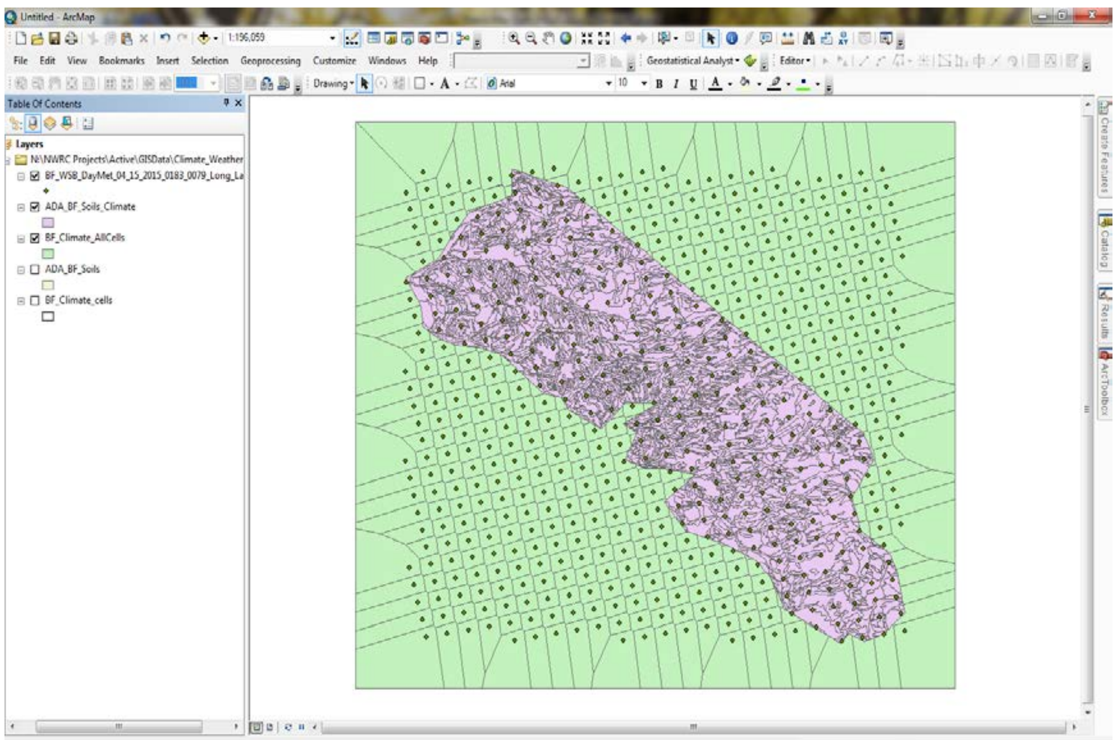
The final stage would be to integrate the Climate file obtained in the Climate data acquisition stage of the input file operation. The procedures will be to correct the projection of the input file using the same projection procedures as before. During this step you will create a Thiessen Polygon of each climate reference point being used and Spatially Joining the attributes of the input climate file to the SOIL to SEA Attribute table.

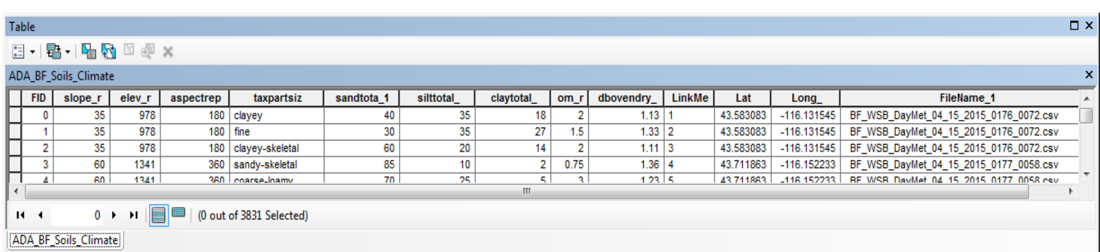


Results

The joins should be sequential and each new join should uniquely include the appropriate field for each characteristic. If successful the end product should be a point file with the three new processed fields appended in a new outputted point shapefile representing the area being characterized. Null values represent areas that were too small for classification or were too close to the edge for reasonable analysis.



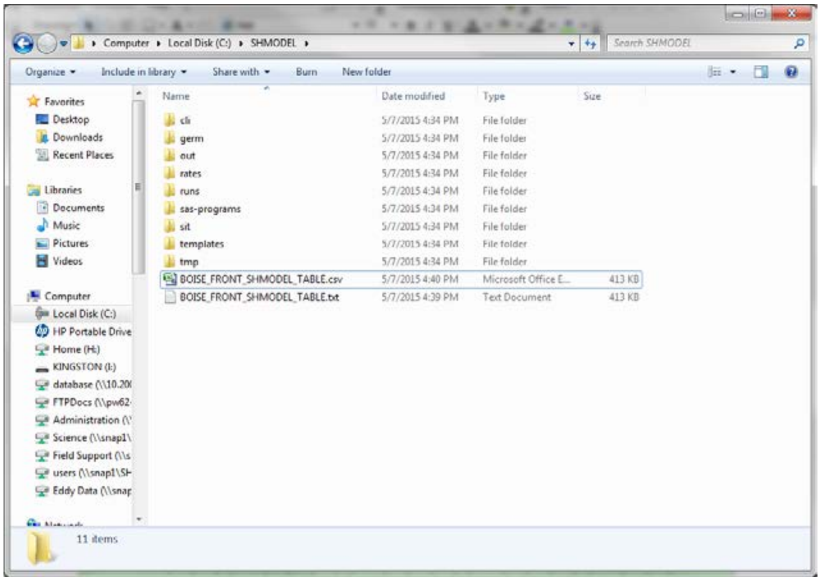




FID	slope_r	elev_r	aspectrep	taxpartsiz	sandtota_1	silttotal_	claytotal_	om_r	dbovendry_	LinkMe	Lat	Long_	FileName_1
0	35	978	180	clayey	40	35	18	2	1.13	1	43.583083	-116.131545	BF_WSB_DayMet_04_15_2015_0176_0072.csv
1	35	978	180	fine	30	35	27	1.5	1.33	2	43.583083	-116.131545	BF_WSB_DayMet_04_15_2015_0176_0072.csv
2	35	978	180	clayey-skeletal	60	20	14	2	1.11	3	43.583083	-116.131545	BF_WSB_DayMet_04_15_2015_0176_0072.csv
3	60	1341	360	sandy-skeletal	85	10	2	0.75	1.36	4	43.711863	-116.152233	BF_WSB_DayMet_04_15_2015_0177_0058.csv

(0 out of 3831 Selected)

From this point export the tables from the attributes window as a text file and save in a directory from which the next stage using SAS will be applied. Once there converting the text file to a .CSV seems to work best for this next stage.



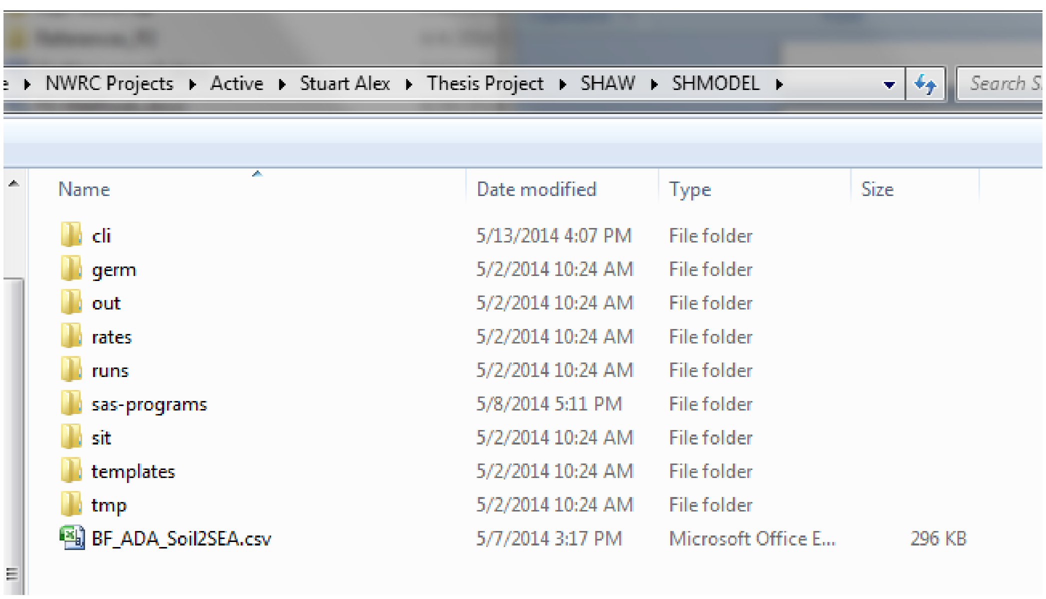
Running SHAW requires a Site file, a reference soil Moisture file, a reference Soil Temperature File, an associated Climate file, and an Input File that directs the SHAW program to the reference states being modeled. Format of these files is very ridged and deviations from where specific inputs are located and nomenclature will result in instant SHAW failure. This process is designed to mitigate most of the potential deviations by automating the creation of the primary reference files and directing the input files to the appropriate climate file for each site specific run. At the end of the process, you will end up with an executable “runme” command file that will run a specific SHAW run for each Soil Polygon characterized in the preceding steps that created the reference table. Upon completion of the SHAW run a specified Hydrothermal Germination model will be run based on the outputted SHAW germination information. The end results will be a germination rate table for each soil polygon modeled that can be summarized into monthly Rate Sum Indices. This information can then be linked back into the original Soil to SEA table using the LinkMe field that is being used as the primary reference for each soil polygon. At that point the data can be projected in a geospatial environment.

Steps for using SAS to run SHMODEL:

Additional steps to building the tables for running in SAS would be to augment the table with some derived values used in some of the input fields. The Site files tend to be fairly complex in construction and some formulas are used in building some of the values for each of the soil layers (nodes). Those nodes will be derived from the adjacent soil texture and bulk density values. In addition, build a table with reference information for the input file. This should include outputs for a site name, climate file name, moisture file name (15bar), temp file name (same as climate). This can be done the same way as the SEA2SOIL was created.

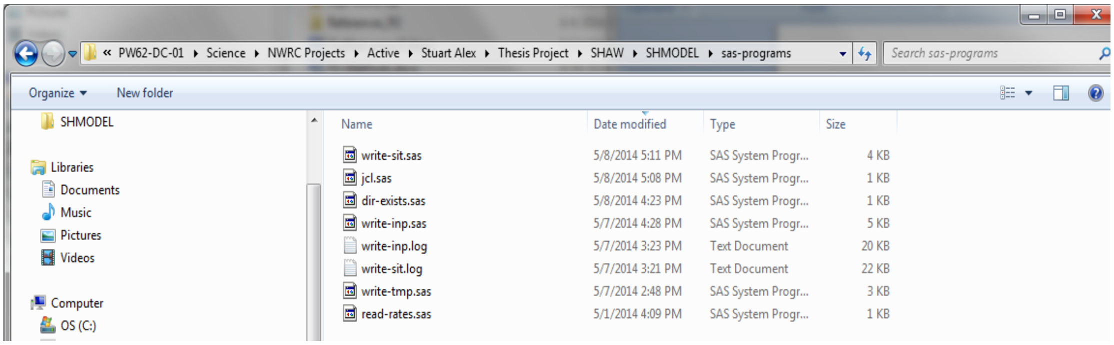
In order to maintain some mechanism of order in how the model worked these files were arranged so that reference data for the model runs and function of the model outputs could be managed separately. For example the Climate folder should contain all the referenced climate data for SHAW. The Climate data is also what is used for generating soil temp (tmp) files which are in turn kept separately.

General File Structure

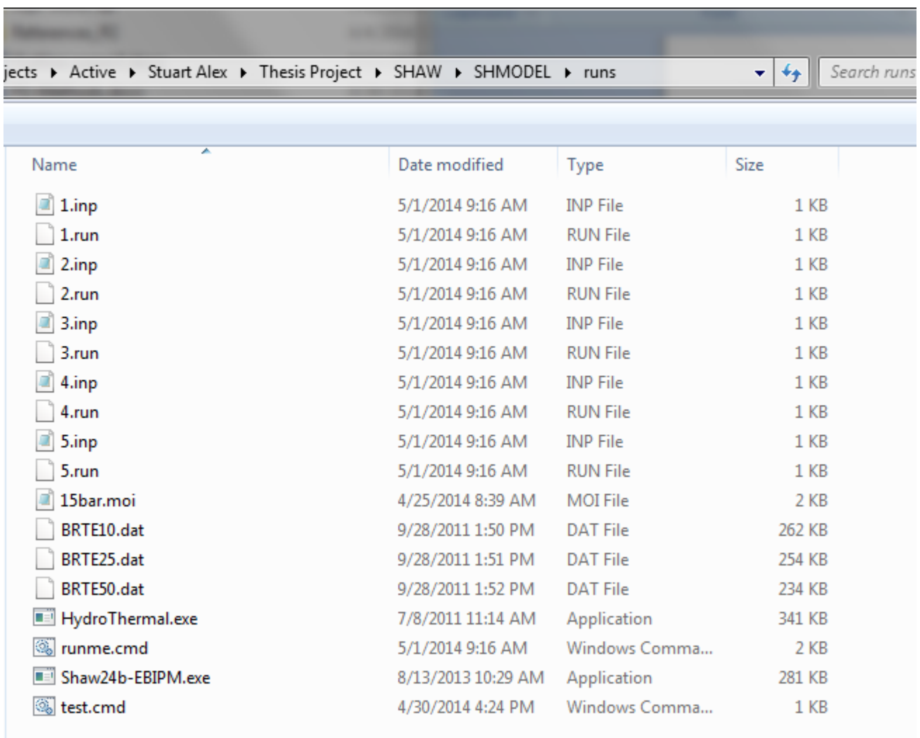


SAS program files:

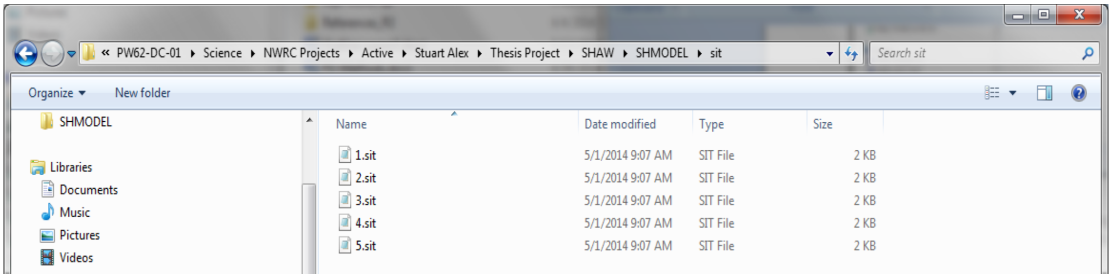
Each of these file generates a specific component for generating input files for SHAW and Hydrothermal. Customizing the outputs of the over-all model occurs here using SAS. In order to modify the run outputs SAS or SAS emulator such as JMP is required.



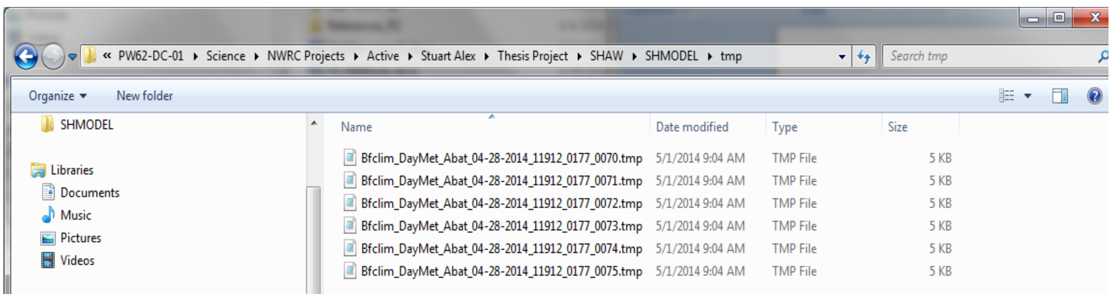
The “Runs” folder is the primary folder needed for doing the individual site runs. Cirtical files for this folder should include the two executables SHAW and Hydrothermal, the reference soil moisture file, and the reference plant species rate files. Once the SAS code is compiled a “runme.cmd” file is generated that will run the completed model.



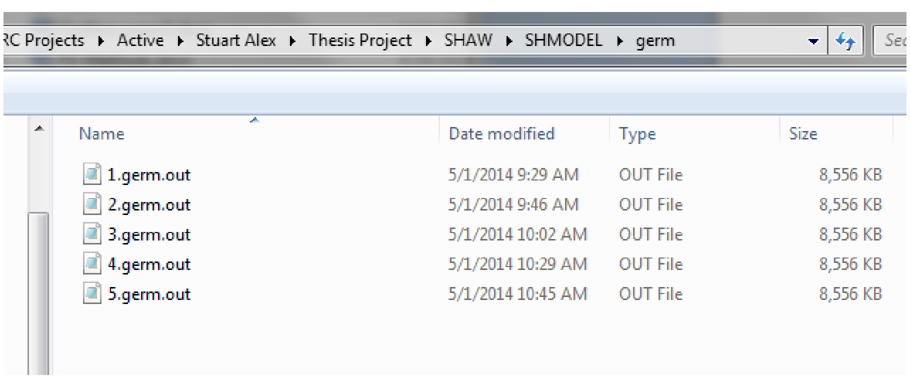
Site files for running SHAW are created by referencing the input Primary file (BF_ADA_Soil2SEA.csv).



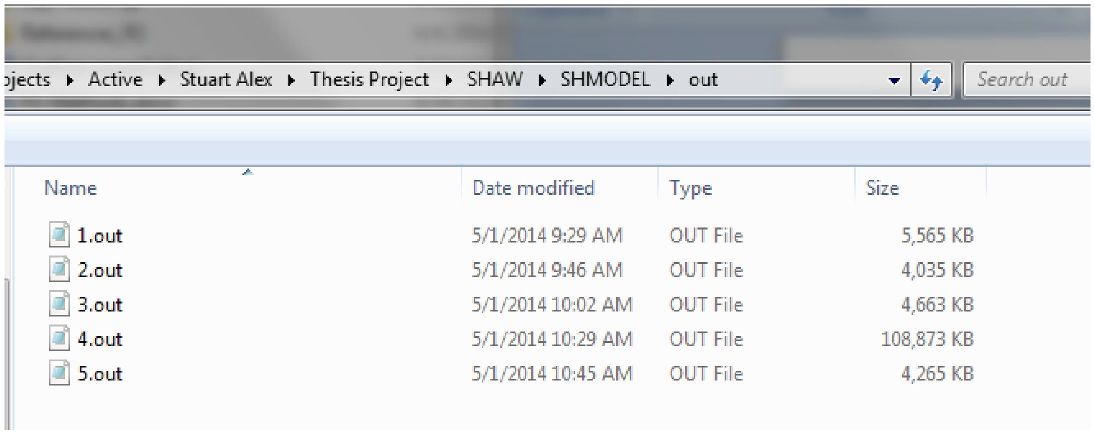
Soil Temperature and Climate files are all dependant on the same directory though little is done with the Climate files themselves in terms of modification. Temp files are stored in a separate directory that is referred to by the input files which are developed from the Primary regional csv file (BF_ADA_SOIL2SEA.csv). The number of temp files will be the same as number of files as there are climate files.



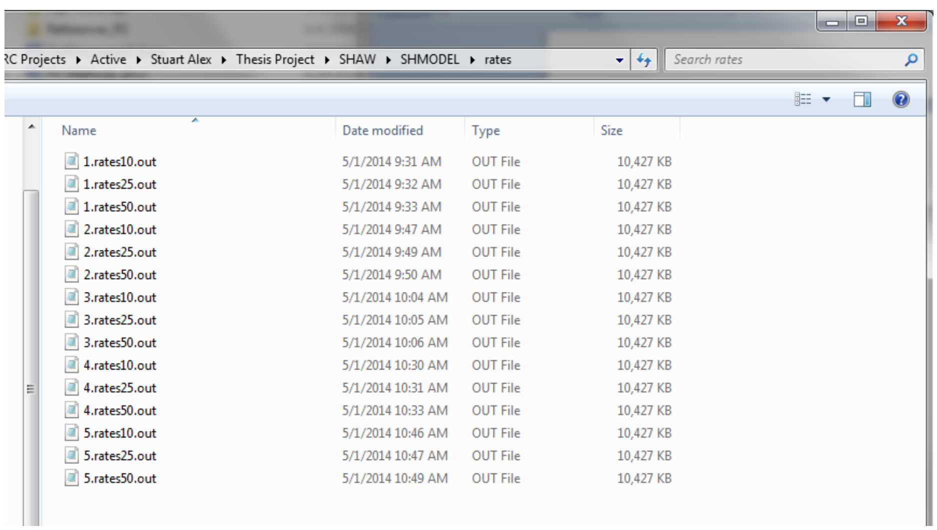
Some folders are meant to retain certain outputs of the models. Germ out folder contains the SHAW output files that are describing the hourly hydrothermal conditions at a 2cm profile. These files are referred to by the hydrothermal model.



Additional data generated that needed to be managed was the Out.out files. SHAW metadata file is called Out is kept in the Out folder. This file is hardwired into SHAW and provides information on individual runs and is helpful for error checking. Though potentially useful for understanding bad runs for SHAW this file is directed into a separate folder.



Rates folder as a repository of each rate file generated from the Hydrothermal portion of the model. Each file represents an hourly rate for a given scenario and is named for a particular reference point in the regional map.



The SAS process involved reading the feature class tables from the GIS generated table and inserting the data into relevant tables for SHAW and Hydrothermal. The SHAW file code entailed preparation of an Input (inp), Site (sit), Moisture (moi), and Temperature (tmp) file for each soil node. Climate data needed for SHAW was obtained using a separate process incorporating a combined daily 1km DAYMET and 4km METDATA (Abatzoglou) file that covers the targeted watershed. Targets for the modeling was a script that will read the GIS table, write text files for each process and run both SHAW and Hydrothermal for each polygon in the watershed.

Once completed a single tool that can run a combined SHAW and Hydrothermal Seed Germination model for a watershed will have been created. Since the output time step is in daily interval of seedling germination rates a monthly average can be generated. Follow up steps still to be resolved is to input the outputted rate files into a single table that contains the unique polygon ID (linkme) for geo-referencing purposes. Determining what problems and inefficiencies can be improved on by applying the model to other regions and potentially running it fully in instead of SAS may also be useful.

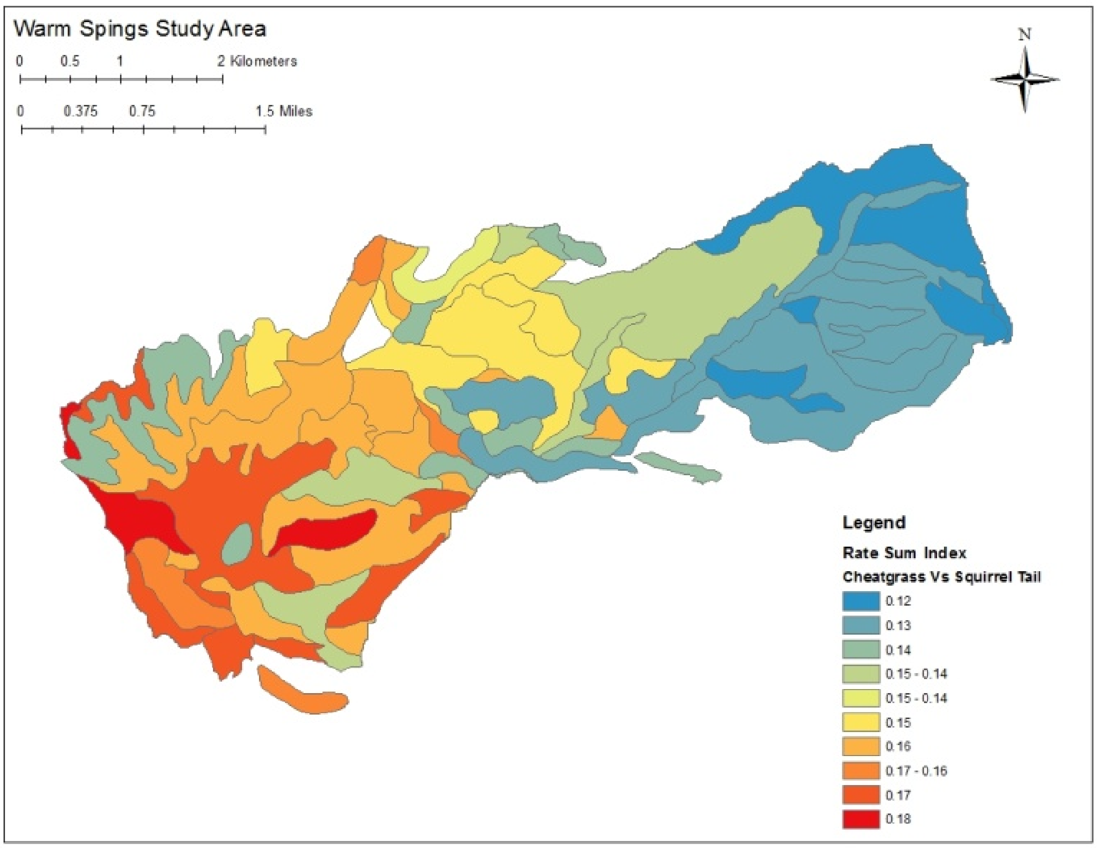


Figure representative output of Germination RSI distribution for a study area in the Boise Front Warm Springs Basin.