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Exploring and Describing the Spatial and Temporal Dynamics of Medusahead in the Channeled Scablands of Eastern Washington Using Remote Sensing Techniques

Timothy M. Bateman
Utah State University

EXPLORING AND DESCRIBING THE SPATIAL & TEMPORAL DYNAMICS OF MEDUSHEAD IN THE CHANNELED SCABLANDS OF EASTERN WASHINGTON USING REMOTE SENSING TECHNIQUES

by

Timothy M. Bateman

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Approved:

Juan J. Villalba, Ph.D. Major Professor	R. Douglas Ramsey, Ph.D. Committee Member
Corey Ransom, Ph.D. Committee Member	Mark R. McLellan, Ph.D. Vice President for Research and Dean of the School of Graduate Studies

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ABSTRACT

Exploring and Describing the Spatial and Temporal Dynamics of Medusahead in the Channeled Scablands of Eastern Washington Using Remote Sensing Techniques

by

Timothy M. Bateman, Master of Science

Utah State University, 2017

Major Professor: Dr. Juan Villalba
Department: Wildland Resources

Medusahead is an unpalatable, aggressive annual that has been invading and degrading western rangelands. This characteristic has negative effects on plant diversity and ecosystem function, promoting the creation of homogeneous landscapes. The costs to wildland systems, agriculture, and the public are high and land managers face resource constraints that can limit successful management. Management plans need to be practical, cost-effective, and sustainable if they are to reach specific targets. Supplementing management plans with remote sensing approaches provide rapid and cost-effective information at the landscape level that is essential for reducing weed invasion. Fast and accurate regional level assessments can alleviate resource constraints by quantifying invasion and modeling dispersal dynamics, which can then allow for more effective and efficient management efforts. There is a knowledge gap in providing an avenue that gets influential information into the hands of land managers in a relatively quick, and cost-effective manner. This Thesis was developed to explore the practicality of using remote sensing techniques as a potential avenue to ascertain influential information on medusahead invasion within a region of eastern Washington challenged by the presence of this weed. I used a multi-scaled approach to develop accurate prediction models to generate spatial and temporal datasets of estimated medusahead cover for an area in the Channeled Scablands region of eastern Washington. These datasets were validated using field data points and a qualitative time line constructed from historical reports of the invasion of medusahead in the area. I was then able to produce/identify: 1) a non-phenological method to predict medusahead cover, 2) temporal dynamics and historical trends, 3) “high risk’ dispersal pathways, 4) climatic variables that influence changes in the time line dataset of medusahead cover, and 5) a strategy map that can be put in the hands of land managers to help direct management approaches to control the spread of medusahead. Research conducted in this Thesis shows the potential benefit of remote sensing techniques to detect trends of weed invasions on rangelands.

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PUBLIC ABSTRACT

Exploring and Describing the Spatial and Temporal Dynamics of Medusahead in the Channeled Scablands of Eastern Washington Using Remote Sensing Techniques

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Medusahead is a harmful weed that is invading public lands in the West. The invasion is a serious concern to the public because it can reduce forage for livestock and wildlife, increase fire frequency, alter important ecosystem cycles (like water), reduce recreational activities, and produce landscapes that are aesthetically unpleasing. Invasions can drive up costs that generally require taxpayer's dollars. Medusahead seedlings typically spread to new areas by attaching itself to passing objects (e.g. vehicles, animals, clothing) where it can quickly begin to affect plants communities. To be effective, management plans need to be sustainable, informed, and considerate to invasion levels across large landscapes. Ecological remote sensing analysis is a method that uses airborne imagery, taken from drones, aircrafts, or satellites, to gather information about ecological systems. This Thesis strived to use remote sensing techniques to identify medusahead in the landscape and its changes through time. This was done for an extensive area of rangelands in the Channel Scabland region of eastern Washington. This Thesis provided results that would benefit land managers that include: 1) a dispersal map of medusahead, 2) a time line of medusahead cover through time, 3) "high risk' dispersal areas, 4) climatic factors showing an influence on the time line of medusahead, 5) a strategy map that can be utilized by land managers to direct management needs. This Thesis shows how remote sensing applications can be used to detect medusahead in the landscape and understand its invasiveness through time. This information can help create sustainable and effective management plans so land managers can continue to protect and improve western public lands threatened by the invasion of medusahead.

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CHAPTER 1

INTRODUCTION

The Channel Scabland region in eastern Washington has seen many landscape altering events in its past. Changing climate regimes, catastrophic floods, and the large-scale conversions of areas for agriculture have helped shape the topography and vegetation communities that they are today. Overgrazing in late 1800s and early-mid 1900s weakened the rangeland plant communities which has allowed exotic annuals to invade. The area has seen large expansions of invasive annuals, like cheatgrass (*Bromus tectorum*) and medusahead (*Taeniatherum caput-medusae*). Believed to be due to a high silica content, livestock tend to avoid medusahead and instead focus grazing efforts elsewhere (Swenson et al., 1964), this in turn selects for large homogeneous landscapes of an annual plant of very poor nutritional quality with the concomitant negative impacts on plant diversity. A high abundance of a specific plant species can produce increased pressures on other members of the plant community, creating a vicious cycle that breeds monotony (Villalba et al., 2015). Additionally, the high abundance of a species like medusahead, can cause increased consumption of other harmful plant species that otherwise might have been avoided. This can cause severe consequences for livestock herds that regularly encounter toxic species, such as lupine (*Lupinus leucophyllus* Douglas ex Lindl. ssp. *Leucophyllus*). Unlike medusahead, cheatgrass is palatable during certain times of the year and has become an integral part of forage communities in western rangelands (Young et al., 1987). Medusahead shows competitive advantages over cheatgrass and has led to its replacement over extensive areas in

Washington. This can add additional pressures to already limited rangelands where carrying capacities for livestock have been reduced by 40-50% (Young & Evans, 1970). Medusahead has also demonstrated advantages in large and infrequent precipitation regimes. Due to this, the belief is that medusahead will be able to continue to expand its range as other species may be more susceptible to the effects of drought (Bansal et al., 2014). Medusahead's ability to displace other vegetation types across a landscape can cause detrimental effects to ecosystem functions that are difficult to reverse. Reductions to plant diversity can lead to changes in the water, nutrient, and fire cycles and can negatively affect the ecosystem services they provide (Costanza et al., 1997; Sheley et al., 2008).

There is an unmet need in research to create ecological models based on dispersal characteristics, which can aid in improving and developing substantial efforts in controlling and preventing the spread of invasive species like medusahead (Davies & Sheley, 2007). Impacts of rangeland weeds can be financially burdensome causing an estimated $2 billion in losses annually (DiTomaso, 2000). Invasions by medusahead can produce financial hardships for ranching operations that may be forced to cut livestock numbers and see substantial increases in management costs (i.e. herbicides, supplemental hay). Costs associated with invasive species often parallel the degree of invasions (Brooks et al., 2004) and can impede management. Large extents of land and limited resources often challenge western land managers. Efforts need to be taken to identify and develop sustainable management practices and programs so management can continue to occur. Prevention has shown to be a more cost-efficient approach compared to reactive and rehabilitation efforts that typically follow invasions (Davies & Sheley, 2007).

Prevention programs aimed at characterizing dispersal behavior need to be developed that allow for early detection and rapid intervention of invaded sites. Computer-based tools, such as remote sensing, can complement and facilitate the development of these types of programs. Remote sensing offers a relatively quick and cheap method to provide assessments of entire landscape systems that would otherwise be difficult, and greatly delayed, using other methods. Remotely sensed imagery has been used to create large scale distribution maps of invasive weeds (Bradley & Mustard, 2005) that can be used by managers to shape management strategies across landscapes. This type of information can save management costs by allowing rapid response to invasion sites, better characterize dispersals traits, and direct management to areas where it would be most effective.

There is a knowledge gap regarding the development of methods for acquiring quick, regional scale information that can allow managers to make informed decisions on the management of medusahead. The present Thesis represents an effort in the direction of bridging such gap: Chapter 2 provides a review of literature related to utilizing remote sensing techniques to explore and describe the spatial and temporal distributions of medusahead in the Channel Scabland region of eastern Washington. Chapter 3 describes the methods used to create a dataset of fractional estimates of medusahead across an extensive area in the Channel Scabland region. This multi-scaled approach integrates ground data and remotely sensed imagery from two platforms to develop a prediction model that estimates distributions of medusahead in the region. Chapter 4 reports on the methods used to create a time line of medusahead distributions in the region. By applying a prediction model to annual Landsat images, a dataset was created that contained estimates of medusahead distributions from 1985-2016. Trend analysis was used to determine trends and magnitudes of changes across space and time. Chapter 5 describes methods used to explore spatial and temporal datasets of fractional estimates of medusahead cover in the region. This chapter shows the practicability of using regional scale datasets to identify dispersal pathways (spatial) and potential climatic drivers (temporal) of medusahead in the Channel Scabland region of eastern Washington.

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CHAPTER 2

LITERATURE REVIEW

THE CHANNELED SCABLAND REGION OF EASTERN WASHINGTON

The Channeled Scabland region has had many land-altering events in its long history. Today, the Channeled Scablands consist of a large network of channels and depressions that have been scoured from basalt bedrock. These occur in eastern Washington and are part of the Columbia River Plateau and Columbia River Basin region in northwestern United States. The Columbia River Plateau is an extensive area that covers southeastern Washington, northern Oregon, and parts of western Idaho. The area is confined by the Blue Mountains to the south, the Palouse hills and Rocky Mountains to the east, the Okanogan Highlands to the north and is drained by the Columbia River to the southwest. The name was derived from the large plateau of Columbia River Basalts which were formed during the late Miocene and early Pliocene. The basalts are associated with volcanic and geological activity occurring during this period and are believed to be related with the early stages of the Yellowstone hot-spot plume, 14-16 million years ago (Pierce & Morgan, 1992). During this period lava poured into this area from cracks and fissures, eventually creating a giant saucer-shaped lava field which tilts to the southwest. Windblown silt deposits began to accumulate on top of the flows and a warm-temperate, summer-wet climate with large conifer and deciduous forests occurred from 18 Ma until roughly 8-4.5 Ma (Leopold & Denton, 1987). During the Miocene, the Cascade Range rose to an elevation that ultimately blocked the existing Pacific weather patterns and formed a rain shadow over the area. This transformed the climate to be summer-dry and eventually altered the vegetation communities from forest to grassland species by the mid-Pliocene (7-8 Ma) (Leopold & Denton, 1987; Blinnikov et al., 2002). By the late-Pleistocene (126,000-5,000 years ago) vegetation consisted of *Artemisia* shrubs and dry adapted grass species (e.g., *Poa, Stipa*, *Festuca* spp.).

The term “scabland” is used in the Pacific Northwest to describe an area where erosive processes have prevented or removed the accumulation of soil and the underlain rock is exposed or covered largely with its own coarse debris (Bretz, 1923). The channeled scablands were carved out of the Columbia River Basalts from cataclysmic floods that occurred during the last Ice-Age. During this period, ice sheets from Canada advanced into the mountainous regions of northern Idaho and Montana. Between 14,000 and 19,000 years ago, the Cordilleran ice sheet formed ice dams on the Clark Fork River which formed the glacial waters of Lake Missoula. Climatic oscillations caused the ice dams to fail, allowing for tumultuous floods speeding westward through the mountain valleys. This occurred at least six-seven times, each break caused glacial water and sediment to be shot-gunned on-to the Columbia River Plateau at speeds reaching 10×10^6 m^3 /s, eventually reaching the Pacific Ocean through the Columbia River drainage (Benito & O’Connor, 2003). These floods are what helped formed the Channeled Scablands region seen today. The rushing flood waters carved large channels in the pre-flood drainages and fissures left in the in the basalt flows. Nearly 2,000 square miles of the basaltic bedrock lost its loessal (recently deposited silty or loamy material) soils from the floods (Bretz, 1969). The deposited lake sediment would continue to be washed down-stream by re-occurring floods until eventually, more profound spillways were formed that began to channel the flood waters to the Columbia River drainage and eventually to the Pacific Ocean. The remnant landscape is now characterized by exposed basalt beds, channels and unscathed loessal island hills of remaining windblown and sediment deposits (Bretz, 1923; Bretz, 1969). These pockets of extremely fertile and productive soils were later recognized by westward settlers for their high vegetation yields and were converted for agriculture practices, such as growing wheat.

Theory suggests that the original inhabitants came down from the western Canadian Rockies about 10,000 years ago, becoming the ancestors of the Nez Perce (Josephy, 1997). The dry climate and limited amount of food sources on the plains, led to most populations centering around rivers. Large ungulate herds didn't inhabit the area, as they did on the Great Plains (Franklin & Dyrness, 1973) and productive hunts on open plains were difficult and scarce. The Nez Perce didn't practice agriculture and relied mostly on fishing and gathering for sources of food. Seasonally, the rivers would fill with salmon from the Pacific Ocean which could be dried and stored for winter months. Certain times of the year would bring plentiful roots, nuts, and berries, which were collected and preserved for winter as well. Horses were absent from the area until 1730, when they made their way north from Spanish settlements in New Mexico. Acquisition of the horse represents the first pressures of intense grazing on the shrub-steppe and grasslands in eastern Washington (Harris, 1991).

During the mid-1800s, European-Americans began traveling through the area as part of the Oregon Trail migration. The rich soils of the plains were recognized for their production potential and permanent settlements soon began in the region. The fertile lands were used to cultivate mostly high quantities of wheat and peas (Franklin & Dyrness, 1973) which eventually found their way downstream of the Columbia River to the prosperous markets of Portland, Oregon. This allowed for a new, wheat-based economy to begin to take form in eastern Washington and populations increased in the region (Schillinger & Papendick, 2008). By the 1870s most of the best farming lands had been converted and settlements began to push into the dryer, untested areas of the scablands region. Here, any fertile soils that could be found were converted to agriculture. The economy boomed in the 1880s when intercontinental rail lines were completed and connected markets across the United States (Granatstein, 1992; Schillinger & Papendick, 2008). The railroads brought with it new farming technologies and migrant settlers who were eager to claim land of their own. People saw opportunities in the recent beef production of English cattle breeds, which had higher quality and production compared to the longhorn breeds of the southwest. These breeds helped increase the beef market and encouraged investments; rapidly increasing cattle numbers in the region (Harris, 1991). With the addition of significant bands of sheep arriving from California, areas that were not being utilized for agriculture were now supporting large herds of livestock. The effects of overstocked rangelands soon took a toll on the plant communities that had evolved in the absence of large grazing herds. By 1904, a USDA employee and a graduate at Washington Agricultural College in Pullman, WA, toured the area and recorded the rangelands to be severely overgrazed (Cotton, 1904; Harris, 1991).

Into the mid-1900s, the plow-horse was traded for the tractor and individuals became educated on conservation and better grazing practices. This helped alleviate some of the grazing pressures which led to improvements on some rangelands (Cholis, 1952; Harris, 1991). Following World War I, wheat demand had dropped and a surplus was built up. This, in combination with multiple years of drought, led to a crash of the agriculture economy in eastern Washington. Following a common pattern in the Midwest, farming became unprofitable and led to over 1 million acres (+ 400,000 ha) of farmlands to be abandoned in Washington (McArdle, 1936). The combination of these highly disturbed, deserted croplands and the weakened rangeland plant communities probably aided in the explosive expansion of rangeland weeds that occurred in the region during the early to mid-1900s (Mack, 1981; McIver & Starr, 2001) which threaten farm and ranching operations today.

Today, management practices, farming techniques and innovative research continues to bring improvements to the area. To better mitigate the limited precipitation, wheat growers in the region typically employ a rotation of tilled summer fallow followed by winter crop (Higginbotham et al., 2013). Wheat and cattle are both in the top 10 commodities for state. The total agriculture production in Washington reached $10.7 billion in 2015 of which $3 billion is from livestock production (USDA-NASS, 2016). The region is almost entirely rancher and farmer owned. Private producers and land managers have continued to evolve, innovate, and expand their knowledge on ways to improve their lands. The continued expansion of successional invasive species presents a constant challenge to farming and ranching in the region. These species continued to persist and threaten the area by altering functional plant communities which put livestock and farming operations at risk.

BIOCTIC & ABIOTIC FACTORS AND THE INTRODUCTION OF INVASIVE GRASSES

The dominant vegetation type in the Columbia Basin during the Miocene were deciduous hardwoods and mixed montane conifer-deciduous forests that showed similarities to the forests of today's eastern United States (Leopold & Denton, 1987). As the precipitation levels dropped and temperatures rose, in response to the developing rain shadow, the vegetation changed to shrub-steppe and Palouse grassland communities. *Artemisia* shrubs and *Poa*, *Stipa* and *Festuca* grasses were better adapted to the xeric climate and expanded through the region (Blinnikov et al., 2002). The morphology of these species evolved differently compared to the heavily grazed caespitose and rhizomatous grasses west of the Rocky Mountains. Large herds of *Bison* spp. and *Cervus* spp. couldn't survive on the plains of eastern Washington. If small herds did exist they would have been restricted to limited areas that supplied continuous summer waters, like the major rivers (Mack, 1981; Leopold & Denton, 1987).

The climate has been compared to the Mediterrane has played a role with the expansion of some exotic weeds. The region is semi-arid and is dominated by dry westerly winds. Winters are cool to cold and moist while summers are warm and dry. Average annual precipitation, for most of the region, ranges from 150mm-300mm with precipitation reaching 550mm in higher elevations to the east and southeast (Daubenmire, 1970; Schillinger & Papendick, 2008). About two-thirds of the annual precipitation occurs from October to March with about one-third of that typically being characterized as snow. A third of the precipitation occurs during April-June with July through September being the driest months (Schillinger & Papendick, 2008).

Land use changes over the past century have resulted in the loss of over half of Washington's shrub-steppe habitat (Dobler et al., 1996). Almost complete conversion to commercial agriculture during the 19th and 20th century has caused the Palouse prairie to be considered as one of the most endangered ecosystems in North America. As much as

99.9 % of the prairie has been lost, with the remaining being threatened by off-road vehicle use, further development, and invasive species (Hanson et al., 2008). Recently, the remaining vegetation communities have been described to contain shrub spp. (*Artemisia tridentata*, *Purshia tridentata*, *Artemisia rigida*, *Artemisia arbuscula*, and *Atriplex confertifolia*), large perennial spp. (*Pseudoroegneria spicata*, *Festuca idahoensis*, *Leymus cinereus*, and *Achnatherum thurberianum),* and alien invaders (*Bromus tectorum*, *Poa pratensis,* and *Taeniatherum caput-medusae*). (Franklin & Dyrness, 1973).

For the last century, invasive annual grasses have threatened agricultural operations, rangelands, and the remaining prairies in the region. Many of the current alien grasses were introduced in the late 1800s and early 1900s as potential new sources of forage for livestock, to supplement the highly depleted rangelands (Mack, 1981). Cheatgrass (*Bromus tectorum)* and medusahead (*Taeniatherum caput-medusae*) have been two of the most prolific invaders concerning the area and likely entered the region from contaminated crop seed or livestock that was being imported to the western states in the late 1800s. One of the earliest records of cheatgrass in the scabland area came from the wheat-growing district of Ritzville, WA in 1884 (Mack, 1986). The overused rangelands in the area offered highly disturbed sites and the reduced competition probably helped facilitate its expansion. In the early 1900s cheatgrass exploded through areas of the West, occupying many overgrazed rangelands. Due to its early spring palatability, cheatgrass was one of the exotic grasses welcomed by parts of the grazing community as an additional forage source on many of the rangelands. Today, millions of hectares in the West are influenced by the invasion of cheatgrass (Young & Allen, 1997).

Medusahead was first reported as an "isolated plant" in eastern Washington in 1901 at Steptoe Butte and the plant was later reported to have been "spreading rapidly" from 1914 to 1940 (McKell et al., 1962). By the 1960's and 1970's medusahead had increased widely and was distributed in semi-arid, steppe regions of southeastern Washington (Daubenmire, 1970; Franklin & Dryness, 1973). During this time medusahead began to replace cheatgrass in extensive areas of Washington, further reducing the carrying capacity of these lands (Hironaka, 1994). The invasion became widespread throughout the state and became a serious risk to rangelands, livestock production, and other agriculture practices. In 2016, the state of Washington listed medusahead as a Type C (highest ranking) noxious weed on the state's Noxious Weed Control Board (WS, 2017). Medusahead has become the dominant vegetation type in large parts of eastern Washington. Extensive research been conducted into better control and rehabilitate methods that aid in preventing further spread through the region (Stonecipher et al., 2016; Stonecipher et al., 2017).

MEDUSAHEAD: HISTORY, BIOLOGY, THE PROBLEM

Medusahead is a member of the *Triticeae* tribe which had likely originated in the Middle East. The tribe of grasses includes known grain crops, such as wheat (*Triticum* spp.) and barley (*Hordeum* spp.). Medusahead is native to the Mediterranean region and seedlings likely entered the western states of the United States through imported crop seed or with livestock. Genetic analysis has suggested, at least seven different introductions have occurred in the West with five occurring in the state of Washington alone (Novak & Sforza, 2008). Medusahead was first reported in the United States near

Roseburg, Oregon in 1887 (Howell, 1903). Although not as explosive as cheatgrass, the plant spread northwest to Washington (1901) and Idaho (1944), south to California (1908), and west to the Great Basin (early 1960s) during the early-mid 1900s (Young, 1992). The plant has been successful in areas which are characterized with similar climates to its native region. Recent estimates have suggested medusahead has now invaded more than 950,000 ha (2.35 million ac) in 17 western states (Duncan et al., 2004; Rice, 2005). The plant has shown advantages over both cheatgrass and ventenata (*Ventenata dubia*) during large, infrequent precipitation events which are believed to support medusahead's continued expanse on western rangelands into the future (Bansal et al., 2014).

Medusahead can extract moisture from extremely dry sites (Young et al., 1999) allowing it to be found on many different soil types, including loamy and the well-drained sandy soils (Kyser, 2014). The plant can be found in the West at annual precipitation regimes from 250-1000mm (Major et al., 1960; Sheley et al., 2008). Medusahead is a challenge to land managers in part because it is principally self-pollinating and can be a prolific seed producer (Young et al., 1968; Young, 1992; Kyser et al., 2014). Medusahead demonstrates phenotypic plasticity, that allows the plant to adapt and compete in many different climates and environments (Young et al., 1968; Young & Evans, 1970; Nafus & Davies, 2014). This helps the species by being able to germinate and produce growth in the fall, winter, and spring when conditions are facilitating. Medusahead has shown advantages in its root development over perennial and cheatgrass seedlings (bluebunch wheatgrass (*Pseudoroegneria spicata* (Pursh) A. Löve); crested wheatgrass *Agropyron cristatum* (L.) Gaertn) during months of December through June (Hironaka 1961). This gives a competitive advantage to medusahead by better allocating resources when they become available through much of its growth period. The largest growth occurs in the spring and maturation generally occurs by July, typically 2 to 4 weeks later than other annual grasses (Young & Evans, 1970; Young, 1992; Nafus & Davies, 2014). Especially in dense stands, medusahead can be distinguished from other plants by color; light green in the spring and bright white/yellow in the summer and fall. The average plant produces multiple tillers and seedheads that help the species remain competitive at invaded sites. The number of seed (caryopses) containing heads per plant is density dependent, with reports stating a single plant per square foot can exceed the seed production of stands of 1000 plants per square foot (Young, 1992; Young et al., 1998; Clausnitzer et al., 1999). The seeds develop long barbed awns that help increase dispersal distances by adhering to passing objects (Monaco et al., 2005; Davies, 2008; Kyser et al., 2014). The awns also can aid in deterring grazing by causing injury to eyes, mouths, and noses of foraging animals (Young, 1992).

Medusahead is of major concern for western rangelands due to physical, chemical, and phenological properties that aid in the plant's ability to change native-fire regimes and drastically reduce biodiversity and forage production on landscapes (Hironaka, 1961; Brooks et al., 2004; Davies & Svejcar, 2008). Medusahead ranks among the highest species of silica accumulating plants and is probably responsible for its resistance to decomposition and much of its unpalatability to animals (Swenson et al., 1964). The slowed decompositions can allow for dense mats of thatch to accumulate which in turn creates an ideal habitat for new medusahead seedlings (Nafus & Davies, 2014). These matted monocultures can quickly alter plant communities by displacing other plant species through competition and suppression of other more desirable species (Bovey et al., 1961; Young, 1992; Young & Mangold, 2008). The thatch layer and dry biomass provide unnatural fine fuels that can increase the fire interval of an ecosystem (Brooks et al., 2004). Increased fires can remove competition and clear and create additional space for reinvasions. The rapid growth and expansion of medusahead, into recently burned sites, can overwhelm, and suppress any re-emergence of less resilient species, like *Artemisia* spp.

Medusahead has replaced large extents of cheatgrass in Washington and other parts of the West (Hironaka 1961; Torell, 1961; Hironaka, 1994). Although cheatgrass is considered an invasive species, over the last century it has become an integral part of early year forage availability for wildlife and livestock on millions of hectares of grazed lands (Young et al., 1987; Young & Allen, 1997). The replacement of cheatgrass by medusahead removes an important source for rangeland production. This displacement of cheatgrass has reduced the carrying capacity of domestic livestock in some areas by 40-50% (Young & Evans, 1970).

MEDUSAHEAD: MANAGEMENT AND COSTS

Management of medusahead includes treatments, such as mechanical, chemical and burning (Kyser et al., 2014). Approaches should consist of multi-year treatments to reduce the viability of seedbanks to prevent regrowth. Generally, the most effective management approaches have come using a combination of treatments. Herbicides are thought to bind to thick thatch layers which can block the chemicals from reaching the soil and reduce the effectiveness of the treatments (Kyser et al., 2007). Research has shown that the control of medusahead invasions can be improved by implementing a burn first, to remove thatch layers, followed by herbicide treatments (Monaco et al., 2005; Sheley et al., 2007). Due to the high probability in highly invaded areas, efforts should be made to rehabilitate treatment areas to prevent reinvasions. If possible, these areas should be revegetated with highly competitive species that can rapidly develop to repel dispersal and reestablishment of medusahead.

Behavior and diet manipulation of livestock has been shown to be a management tool which can allow for the targeting and utilization of plant communities to achieve pre-determined objectives (Villalba et al., 2015). Although unpalatable, Stonecipher et al. (2016) was successful in using diet manipulation to increase consumption of annual grasses (including medusahead) by cattle. The authors reported that, although the effects may be influenced by animal type/size, diet manipulations with protein supplements can enhance the intake of annual species by cattle which may provide a useful tool in medusahead management.

The costs of introduced weeds to agriculture in the United States have been estimated to exceed $36 billion annually (Pimentel et al., 2000). The impacts on rangelands is estimated at $2 billion in losses (DiTomaso, 2000), with costs generally increasing with increased invasion levels (Brooks et al., 2004). Weeds continue to present challenges that can cause ecological and economical losses to land managers, farmers, and ranching operations by decreasing biodiversity, reducing crop yields, and increasing operational cost (DiTomaso, 2000; Duncan et al., 2004; Pimentel et al., 2005). Ranchers can see direct costs coming from reductions in the quantity and quality of livestock forage, diminishing property values, added supplemental cost, and costs associated with weed control (i.e. herbicides). Additionally, livestock's preference of a species may not depend on nutrition and secondary compounds alone, but can also be influenced by the quality and abundance of other species in a plant community (Villalba et al., 2015). This can lead to serious implications for areas like the Channeled Scablands region. This region has been challenged by cyclic episodes of a high abundance years of velvet lupine (*Lupinus leucophyllus* Douglas ex Lindl. ssp. *Leucophyllus*), which can cause crooked calf syndrome and devastate an operation's financial income (Ralphs, et al., 2006; Ralphs et al., 2011). The high abundance of low quality medusahead may in turn influence and increase the palatability of the velvet lupine. This could potentially provide serious consequences if herds begin to seek out the toxic species as a better forage alternative.

Medusahead is becoming more noticed for its rapid coverage and detrimental characteristics to rangelands productivity and historic carrying capacities. In some cases, a dramatic reduction of 50-80% in grazing capacity can develop in just a few years (Hironaka, 1961). Increased fire frequencies would also drive up costs associated with fighting fires and the subsequent rehabilitation efforts (Torell et al., 1961; Duncan et al., 2004). Reduced biodiversity due to medusahead can result in changes to the historic functioning of ecosystems that can be difficult to reverse. A decrease in plant diversity can lead to reductions in soil nutrients, change water and nutrient cycles, and decrease below ground carbon storage (Davie & Svejcar, 2008). These changes have consequences for wildlife habitat and cause damage to populations of special interest species, such as the greater sage grouse (*Centrocercus urophasianus*).

The control and rehabilitation of medusahead invaded sites are both costly and time intensive and can often be unsuccessful if the original management practices and behaviors are not changed (Davies et al., 2010; Kyser et al., 2014; Nafus & Davies, 2014). Higher costs are associated with heavier invasion levels and the probability of success of treatments begins to decline with the increasing invasion levels (Brooks et al., 2004; Nafus & Davies, 2014). Because of the high costs associated with the control and rehabilitation efforts, prevention efforts are becoming recognized as more viable and cost-efficient options (DiTomaso 2000; Davies, 2008; Young & Mangold 2008). High cost cause management plans and objectives to become limited and unsustainable. It has been estimated that for every dollar management spends on preventive and control efforts, it saves $17 in later expenses (Davies & Sheley 2007).

Healthy and intact systems have been suggested to reduce the performance of medusahead and provide fitness support for native and more desirable species (Daehler, 2003). Additionally, tall wheatgrass species may be able to impede seed dispersal and reduce establishment of medusahead seedlings (Davies & Sheley, 2007; Davies et al., 2010). Management plans need to explore and utilize developing systems that repel invasions. This will help develop programs that are aimed at promoting proactive, rather than reactive weed management strategies. These programs in conjunction with strong educational campaigns should be developed and evaluated so that the remaining medusahead-free rangelands in the West can be conserved (DiTomaso, 2000; Davies, 2008; Young & Mangold, 2008).

REMOTE SENSING APPLICATIONS AND INVASIVE WEEDS

There are a variety of different platforms and sensors that remotely collect spectral information of natural resource systems around the world. Imagery, provided by drones, aircrafts and satellites, can provide large amounts of information by measuring large areas outside of traditional sample plots, commonly assumed to be representative of the conditions present in heterogeneous landscapes (Hunt, et al., 2003). This large-scale information can be used by land managers to explore the spatial dynamics of entire landscape systems. Additionally, image collections repeated weekly, monthly, or annually can be analyzed as an avenue to detect changes and gain valuable information on past trends of forest and rangeland systems (Vogelmann, et al., 2012). Immediate information, from analyzing archived imagery, can lead to the discovery of troubled systems more quickly compared to traditional change detection methods which are typically limited by future measurements. This relatively rapid acquisition of data can allow managers to make timely changes to the conditions of their operations.

Remote sensing analysis can allow for huge advantages where research is financially and spatially limited. Homer et al., (2012) integrated field measurements and three remote sensing platforms to produce predictions of rangeland components (bare ground, herbaceous, litter, shrub). With an average Root Mean Square Error (RMSE) of 8.02, the authors produced predictions at three spatial resolutions (2.4m, 30m, 54m) of each component across extensive areas of Wyoming in the United States. Sant et al., (2014) utilized millions of millimeter data points from ground-based color vertical photography (GBVP) to construct continuous measurements of rangeland components. At an average R^2=0.86 the authors used Regression Tree analysis to integrate data points from GBVPs and remotely sensed imagery (1m, 30m) to make spatial and temporal predictions. These types of applications can allow for the acquisition of information on every square meter of a landscape and provides access to areas that would be difficult to access from the ground.

Remote sensing applications have been used to explore and characterize both spatial and temporal distributions of invasive weeds. Bradley & Mustard, (2006) were able use an image subtraction method to create cheatgrass occurrence maps for 28,000 km^2 in northern Nevada. The authors used these datasets to predict invasion probabilities, identify “high risk” areas, estimate expansion rates, and identify anthropogenic features associated with high levels of cheatgrass (e.g., power lines, cultivation, roads, etc.). Rivera et al., (2011) used sampled cheatgrass and non-cheatgrass sites to identify and model environmental variables that were associated with cheatgrass invaded locations. This was used to identify current and future locations that were at a “high risk” of invasion from cheatgrass. This data could then be used in conjunction with habitat and distribution models to generate sensitive areas for threatened wildlife species. The type of information that can be achieved from applications like these could be handed over to land managers, so they can make informed decisions and direct management to protect areas challenged by the invasions of destructive species, so western rangelands can be safeguarded.

A key to successful management is a robust and sound understanding of a target species. Remote sensing applications can provide valuable information that can lead to improved invasion models that could benefit preventative efforts (Rocchini et al., 2015). Regional distribution maps can help provide risk assessments, educate the public and government officials, gather support and funding, and prioritize management (Bradley & Marvin, 2011). Land managers are currently facing limited resources as they try to make management decisions on large extents of western public lands. If managers could become equipped with these types of maps, then large areas could be inventoried, monitored, and evaluated; leading to more informed decisions by land managers that account for entire ecosystems. Remote sensing provides an avenue for managers to become more effective and management to become more cost-efficient, so sustainable, educational, and prevention programs can be developed, allowing for additional lands to be rehabilitated and preserved.

WHAT NEEDS TO BE DONE

Medusahead is a destructive and aggressive invasive species that will continue to degrade western lands unless effective control and prevention techniques can be identified and implemented. Individuals need to be concerned with the serious implications and consequences that come from the continued expansion of this species throughout the West. Management can quickly become limited by resources, allowing for invasions to reach detrimental levels that are difficult to reverse. Initiatives need to be taken to educate the public, government officials, and the ranching communities of the dangers of invasions and common vectors of medusahead so new invasion sites can be limited. Research into successful management strategies needs to continue so that land managers can develop sustainable and improved control and prevention methods. Because medusahead demonstrates phenotypic plasticity, management may require site specific research to achieve highest levels of success and efficiency.

There is an unmet need to provide land managers with site specific ecological models that aid reducing costs while improving control and prevention efforts of medusahead management. Remote sensing techniques can provide a valuable and unique tool in the manager's toolbox that can supplement and complement current medusahead management plans on western rangelands. Information that can be provided by remote sensing technologies can help with early detection of troubled systems and an ability to assess and direct management needs. This type of information can aid in developing more sustainable, effective, and efficient management programs so the protection and rehabilitation of western rangelands can continue.

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CHAPTER 3

A MULTI-SCALE APPROACH TO PREDICT THE FRACTIONAL COVER OF MEDUSAHEAD (*Taeniatherum caput-medusae*) IN THE CHANNELED SCABLANDS OF EASTERN WASHINGTON

ABSTRACT

Medusahead is an aggressive, winter annual that is of dire concern for the health and sustainability of western rangelands. Medusahead reduces plant diversity, alters ecosystem function, and reduces carrying capacities for both livestock and wildlife. The Channeled Scablands of eastern Washington represent a typical example of a region being challenged by the expansion of this weed. The costs of the invasion are high and financial constraints can limit successful management. Managers need the ability to identify medusahead across entire landscape systems, so they can work towards effective and efficient management approaches. Remote sensing offers the ability to measure vegetation cover at large spatial scales, which can lead to a better understanding of the invasive characteristics of problematic species like medusahead. For instance, research has been successful in creating large-scale distribution maps of cheatgrass over western rangelands. Despite this advancement, many applications rely on the phenological characteristics of a target plant that can present problems for separating two species with similar phenologies (i.e. cheatgrass & medusahead). This study integrated GPS field points from three study sites (Sites S, C, & N) and imagery from two remote sensing platforms, to delineate, model, predict, and validate medusahead cover estimates over 37,000+ hectares (91,000+ ac) of rangelands in the Channeled Scabland region of eastern

Washington. Using a multi-scaled approach, this research showed that regression tree models can identify complex spectral relationships of senesced medusahead cover using late summer Landsat scenes. The predictive performances resulted in a R^2 of 0.80 near the training site (Site S) and a R^2 of 0.68 away from the training site (Sites C & N). This research provides potential for a non-phenological approach to produce accurate large-scale, distribution maps of medusahead. The performance results show the need to incorporate spatially rich training data when developing prediction models. This research reveals a non-phenological method that can put data rich information in the hands of land managers who can then make informed decisions to help improve western rangelands challenged by the invasion of medusahead.

1. INTRODUCTION

Medusahead (*Taeniatherum caput-medusae* [L.] Nevski) is an invasive winter annual grass that has invaded more than 973,000 ha (2.4 million ac) in 17 western states of the United States (Rice, 2005). Medusahead is of major concern for western rangelands due to physical, chemical, and phenological properties that enable the plant to alter fire regimes and drastically reduce forage production as well as plant diversity (Hironaka, 1961; Brooks et al., 2004; Davies & Svejcar, 2008). In addition to wind dispersal, long awns are adapted to adhere to passing livestock, wildlife and vehicles which can carry seeds great distances (Sharp et al., 1952; Monaco et al., 2005). Due to its rapid growth and the ability to form dense mats of thatch, medusahead can quickly alter plant communities by displacing other plant species through competition and suppression (Bovey et al., 1961; Young, 1992; Young & Mangold, 2008).

The impacts of invasive weeds have been recognized as a serious economic problem for rangelands in the United States (Duncan et al., 2004; Pimentel et al., 2005); with estimates of $2 billion in losses annually (DiTomaso, 2000). Alterations and degradation of rangelands from invasive weeds can directly impact livestock producers by lowering both quantity and quality of forage, decreasing property values, and increasing management and production costs (DiTomaso, 2000). Control, treatment, and, rehabilitation of medusahead invaded sites are both costly and time intensive and can often be unsuccessful if land use practices and behaviors are not changed (Davies, 2010; Kyser et al., 2014; Nafus & Davies 2014). Proactive, sustainable programs aimed at prevention and education need to be developed and evaluated to conserve the remaining medusahead-free rangelands in the West (DiTomaso 2000; Davies, 2008; Young & Mangold 2008). Such programs would prove to be advantageous to land managers and producers by prioritizing management efforts on invaded and pre-invaded land.

Remote sensing technologies offer an economical and practical tool to model vegetation distribution and dispersal across large portions of rangeland that often isn’t achievable with traditional field-based methods (Xie et al., 2008; Rocchini et al., 2015). Like medusahead, *Bromus tectorum* (downy brome; cheatgrass) is another early growth, winter annual that has been invading several ecoregions in western rangelands (Hironaka, 1961; Young et al., 1987). In recent years, remote sensing methodologies have shown success in estimating detecting and formulating invasion probabilities of cheatgrass over large portions of the western states in the United States (Bradley & Mustard, 2006; Clinton et al., 2010; Boyte et al., 2015). The methods generally utilized rely on the phenological traits of early greening/early senescence. These methods prove to be problematic for researchers or land managers interested in delineating different annual species that share similar phenological characteristics i.e., cheatgrass and medusahead.

New, large-scale methodologies that model, predict, and quantify invasive species, like medusahead, are lacking but are urgently needed (Peterson & Vieglais, 2001; Davies & Sheley, 2007a). Success at accomplishing such a goal, using remote sensing, can prove to be difficult due to the variety of platforms offering different strengths and weaknesses. For example, High-resolution imagery (0.5-2.0 m) may be useful in species identification but often can be too financially constraining if a larger assortment of spectral bands is needed (Xie et al., 2008). Regression Trees (RTs) are rule based models that can be used to identify correlations between dependent and independent variables (Xian et al., 2013). RTs have proven to be useful in ecological research for integrating strengths of various platforms to model and predict fractional estimates of rangeland components (Homer et al., 2012; Sant et al., 2014; Xian et al., 2015). Fractional estimates provide continuous datasets that can allow for an ability to better detect gradual temporal and spatial distribution shifts while representing a more realistic and robust description of dispersal characteristics of specific components (Fernandes et al., 2004; Wegmann et al., 2016). An ability to analyze fractional estimates can aid in gaining timely information while management can still be influential. Additionally, continuous datasets can help prioritize management areas which can provide avenues for reducing costs while improving control and prevention strategies for medusahead spread.

The objective of this study was to use remote sensing techniques to develop a method that delineates, models, and predicts fractional estimates of medusahead in the

Channeled Scabland area of eastern Washington. Using strengths of two imagery types, this study's hypothesis was that medusahead patches could be classified during its senescent form, allowing for a multi-scaled approach to be used to identify and model the spectral characteristics of medusahead so fractional estimates can be predicted over a relatively large portion of rangeland.

2. STUDY AREA

The study was conducted within the Channeled Scabland region of eastern Washington and consisted of 37,178 hectares (91,868 ac) of rangelands southeast of Ritzville, WA (46°48.23'N, 118° 16.98'W; 434 m). The vegetation community was once categorized as steppe and shrub-steppe with climax communities being dominated by *Artemisia tripartita*, *Agropyron spicatum* and *Festuca idahoensis* (Daubenmire, 1970; Franklin & Dyrness, 1973) but it is now dominated by annual grasses, such as cheatgrass and medusahead; and weedy forbs fiddleneck (*Amsinckia intermedia* Fisch. & Mey), tansy mustard [*Descurainia pinnata* (Walt.) Britt.], rush skeletonweed (*Chondrilla juncea* L.), black mustard [*Brassica nigra* (L.) Koch in Roehl], and filaree [*Erodium cicutarium* (L.) L'Hér.] (Ralphs et al., 2011). Areas with wheatgrass species ([*Pseudoroegneria spicata* (Pursh) A. Löve], [*Agropyron cristatum* (L.) Gaertn], [*Thinopryum ponticum* (Podp.) Z.-W. Liu & R.-C. Wang]) and basin wildrye [*Leymus cinereus* (Scribner & Merrill) A. Löve] are present in the region but are scarce.

The climate is semiarid with a 50-year average annual precipitation of 272 mm (NOAA, 2017). The elevation slopes from the north to south and ranges from 600m to 323m. Large elevated areas, which are generally 45-75m above the surrounding rangelands, tend to increase in frequency moving further south. The tops of these areas have deep, high-quality soils and are typically used for agricultural production, while the surrounding areas are generally used for grazing livestock and are scattered with agriculture and urban developments.

Extensive grazing and repeated fires have led to many areas becoming dominated by annual species (Daubenmire, 1970; West & Young, 2000). Today, the competitive ability of medusahead has displaced many areas once dominated by cheatgrass which has led to medusahead becoming the dominant player in large portions of eastern Washington (Hironaka, 1994). Since the 2000s, herd sizes in the area have been reduced in some cases by 50% and producers have had to change historic practices to mitigate losses from the invasion. These changes include: adding additional farming operations, altering historic grazing practices, modifying calving strategies, and increasing supplemental forage (Information gathered by interactions with producers from the region).

2.1. Site Descriptions

The analysis was conducted at three sites spanning over a 33 km transect. This was done to take advantage of any variations in rangeland conditions and environmental factors while providing independent test sites for the prediction model. Site S was located about 26 km southeast of Ritzville, WA (47°03.16’N, 118°02.79’W, 553 m). The site consisted of approximately 3,209 ha (7,930 ac) of grazed rangelands with roughly 187 ha (462 ac) being a part of the United States Department of Agriculture (USDA) Conservation Reserve Program **(**CRP). The soil taxonomy falls into Benge gravelly silt loam and Loamy to Coarse-loamy, mixed, superactive, mesic typic and lithic haploxerolls

(Anders-Kuhl extremely rocky silt loams). Site C was located about 26 km south of Site S (46°50.29’N, 118°09.99’W, 469 m) and consisted of approximately 60 ha (148 ac) of grazed rangeland. The soil classification is the same as Site S (Benge gravelly silt loam). Site N was located 33 km south southwest of Site S (46°48.23’N, 118° 16.98’W, 434 m) and consisted of approximately 73 ha (181 ac). The soil taxonomic class is a coarse-loamy over sandy or sandy skeletal, mixed, superactive, mesic calcidic haploxeroll (Stratford silt loam).

Loessal mounds are scattered throughout the area (Daubenmire, 1970) and were present at all three sites. The mounds were heavily dominated by medusahead, and in some cases cheatgrass. The mounds were noticed in both circular and linear forms ranging from 1-80m^2 and sometimes running 500m in length. They were about a meter higher than the surrounding area and would be generally spaced 7-15m apart.

3. MATERIALS AND METHODS

A non-phenological method was developed that integrated: field collected data, 1-meter National Imagery Program (NAIP) and 30-meter Landsat Operational Land Imager (OLI). This allowed for senescent medusahead to be identified using High-resolution imagery and then modeled using a larger assortment of spectral bands of the coarser imagery to produce fractional estimates of the plant for every 30 m^2 pixel throughout the study area. Site S was used as the training site for the model because it showed the most variation in rangeland components and supplied a sufficiently larger dataset compared to the two other sites. Sites C and N were used to measure the model’s predictive performance away from the training area.

3.1. Field Sampling

Field data was collected in the fall of 2015 when most of the rangeland vegetation was dormant or senesced. Land cover and vegetation types were categorized into six component classes: bare ground; tall perennials; medusahead; cheatgrass; upland (*shrubs, herbaceous*); and other (*e.g., riparian vegetation or basalt outcrops*). A data collection platform was developed to link a handheld GPS to a smartphone, so the user could record locations, photographs, and field observations (ESRI, 2017). The platform allowed the user to record continuous real-time locations in addition to discrete locations. Continuous data collection allowed the user to walk around outer extents of components, creating bounding polygons that were used to help identify component types on an image. The discrete locations were used to validate the post-classification outputs at each site. All locations were recorded within 1.3 km of improved roads.

Locations which were dominated by different rangeland components were geo-located using a high precision GPS Trimble R1 GNSS receiver using the satellite-based augmentation system (SBAS), so that optimal performance would be achieved. Locations were identified by strategically walking through different portions of the sites, identifying uniform rangeland components greater than $1m^2$. This was done to assure a wide range of landscape forms and vegetation types were used to train and test the classification model (Peterson, 2005; Jiapaer et al., 2011). At each location, the user would: (1) verify the GPS receiver was receiving optimal precision (generally 55-80cm); (2) record the position at the center of the uniform patch; (3) document the dominant vegetation or land cover component; (4) attach a photograph of the patch and surrounding area; (5) document any beneficial observational standards or anomalies present. At some locations, instead of recording a discrete point, the spatial extents of homogeneous components were outlined by recording continuous positions as the user walked around the patch. This provided a bounded polygon that was used to later help identify components on the NAIP image. All geo-reference data were projected into the UTM zone 11 NAD83 coordinate system.

3.2. Supervised Classification

Supervised classifications were done independently for each site using a NAIP image that was acquisitioned on July 02, 2015. The image was comprised of four spectral bands consisting of red, blue, green, and near-infrared. The Digital Ortho Quarter Quads (DOQQs) were mosaiced, projected to the UTM zone 11 NAD83 and clipped to the study area. Agricultural developments, areas with urban structures, and large elevated areas and their associated drainages, were masked by digitizing excluding polygons on the NAIP image.

One-meter NAIP pixels were classified into either a present or absent class of medusahead monoculture (binary response) using the Visual Learning Systems Feature Analyst Software ™ 5.2.0.0 classification software (2015). The continuously recorded field polygons along with knowledge gained of occurring spatial distributions from field sampling, aided in identifying, to the user, specific spectral and textural characteristics of medusahead and other components on the NAIP image. This essentially trained the user to the appearance of the binary classes on the NAIP image. The user scanned the NAIP image and identified sample areas for each of the binary classes to extract "training" pixel values for the classification software. The values of these areas were extracted by digitizing polygons around the extent of an identified class. A minimum of 20 digitized polygons, generally $5m^2$, were created for each of the two classes at each of the three sites. The software automatically created a classification model from the extracted, “training”, pixels. The model correlated unique spectral and spatial signatures for each of the binary classes which was then used to extrapolate classifications to the remaining pixels of that site (Blundell & Opitz, 2006). This was done using the "Land Cover Feature" and "Manhattan Input Representation" options in the Feature Analyst Software (2015).

3.3. Fractional Cover

Fractional cover (fCover) analysis was used to integrate the 1-meter post-classifications and a 30m Landsat image independently at each site. A vector shapefile was created from the extents of Landsat pixels of each site. This formed 30m x 30m bounded boxes which were then used to calculate proportional data of the present medusahead binary class from the classification output. Proportions of medusahead were calculated for each Landsat pixel by dividing the number of 1-meter present class pixels by the total number of pixels that were available (n=900).

$$One\ fCover\ pixel = \frac{\#\ of\ mh\ pixels}{900}$$

This created a continuous dataset of fCover values for medusahead at 30m resolution that would be then used to train and test the prediction model.

3.4. Predicting Fractional Cover

A prediction model was developed characterizing relationships between the fCover pixel values and their associated Landsat reflectance values. The Path43/Row27 image, acquisitioned from the Landsat 8 satellite on August 05, 2015, was downloaded from the United States Geological Survey, Earth Explorer website (USDI-USGS, 2016). The image was projected to the UTM zone 11 NAD83 coordinate system, clipped, rescaled to TOA percent reflectance (Landsat, 2016) and normalized for sun angle. There were 36 predictor variables used which were derived from the Landsat image and consisted of: six Landsat bands (band 2, Blue, 0.450-0.515µm; band 3, Red, 0.525-0.600µm; band 4, NIR, 0.630-0.680µm; band 5, $SWIR_1$, 0.845-0.885µm; band 6, $SWIR_2$, 1.560-1.660µm; band 7, 2.100-2.300µm), six tasseled-cap outputs (Baiga et al., 2014) and 23 different ratio indices and spectral combinations (See Table 3.1). All the ratio indices and spectral combinations were created using reflectance values from Landsat bands: 2, 3, 4, 5, 6, 7.

Modeling was done using a sampled dataset consisting of fCover pixels that were randomly stratified into 11 bins from the overall population at Site S. The bin thresholds were 0, 1, 11, 21, 31, 41, 51, 61, 71, 81, 91 and 100 percent. From this dataset, a sub-sample was subset for an independent test, using the same 11 bins. The remaining data was used to train the prediction model. Stratified sampling was chosen to assure all extreme values would be represented and to ensure the model was robust enough over the entire range of fCover values (0-100%) (Homer et al., 2013; Sant et al., 2014; Boyte et al., 2015). The training dataset, of fCover pixel values, was used as the dependent variable and their associated input variables as the independent variable. Four types of machine learning, RT algorithms (Classification and Regression Tree CART; Random Forest; Stochastic Gradient Boosting; Cubist), were evaluated for their predictive performance. RTs were used to “mine” the training data to discover complex relationships between the dependent and independent variables. These relationships were modeled and used to generate predictions outside of the training dataset

Modeling was done using R (R Development Core Team, 2016) and the rpart (Therneau et al., 2013), randomForest (Liaw & Wiener, 2002), gbm (Ridgeway, 2015), Cubist (Kuhn et al., 2016) and caret (Kuhn, 2017) R packages. Multiple trials were performed to identify the proportion of sampling data (Homer et al., 2013), the RT algorithm, and RT tuning parameters (Kuhn & Johnson, 2013) that optimized prediction performance. To save on computational time, initial trails were assessed using 5-fold cross-validations (CVs) while later trails were assessed with more computational intensive 10-fold (CVs). Independent tests, and visual inspection of outputs were later used to assess performances. Because negative or estimates greater than 100 percent cannot be possible, any post-prediction that produced a value below zero or above 100 percent were converted to zero or 100 percent, respectively.

3.5. Model Evaluations

The supervised classifications and prediction estimates were evaluated using different approaches. Geo-located field points, visual comparisons of field photos and visual assessments were used to evaluate the classification outputs while prediction estimates were evaluated using a 10-fold CV, independent tests, and visual inspection of the final prediction map.

3.5.1. Supervised Classification

The accuracies of the 1-meter classification outputs were validated using the geo-located points, which were collected following the *field sampling* protocol. This was done by visually assessing whether each recorded discrete location was successful or unsuccessful in predicting the class of the underlying pixel. In addition, a location was reported to be successful if the underlying pixel was misclassified but an adjacent pixel was correctly classified. This was believed to be an acceptable action due to occurring issues of locations falling relatively close to the bounding extent of neighboring pixels, the inherent errors of the GPS receiver and the true alignment of the NAIP image. The overall accuracies as well as the user accuracies and the producer accuracies of the outputs were calculated and reported for each site using a confusion matrix. Final classifications were assessed visually by referencing field photos and knowledge of spatial distributions in the area.

3.5.2. Regression Tree Predictions

The metrics used to evaluate prediction performances were Root Mean Squared Error (RMSE) and the correlation determination (R^2). The RMSE is a measurement of the variance between the predicted and observed values and it is reported in the same units as the modeled variable. The R^2 is a number representing a measurement of the amount of total variation that can be explained by the model (0, no variation explained; 1, all variation explained). Both metrics have been used in ecological research using remote sensing, as a measurement of prediction performance (Boyte et al., 2015; Homer et al., 2013; Xian et al., 2013). To assure repeatability the final model was assessed using a 10-fold CV repeated 10 times. Independent tests at each site (n=3) were then used to evaluate the final model and were reported as a characterization of the prediction performance. The independent tests were evaluated by regressing the observed and predicted values using the R environment (R Development Core Team, 2016). Identifying an appropriate accuracy threshold was done by assessing R^2 values from past research predicting similar rangeland components (Peterson, 2005; Sant et al., 2014; Xian et al., 2015). The threshold of a $R^2 > 0.75$, for the independent test at Site S, was used to characterize an acceptable predicting performance.

4. RESULTS

4.1. Supervised Classification

The results from the supervised classification accuracy assessments are reported in Table 3.2. Site S produced the highest overall accuracy of 97.0%, showed the highest producer's accuracy of 96.0% and produced a user's accuracy of 92.3%. The classification showed that 1,053 ha (2,602 ac) were dominated by medusahead. Site C produced an overall accuracy of 92.9%, a producer's accuracy of 85.7% and the highest user's accuracy of 100.0%. The classification of site C showed 28 ha (148 ac) which were dominated by medusahead. The Site N classification showed the least performance, showing the lowest overall accuracy of 88.9%, and the lowest producer's accuracy of 75.0% and user's accuracy of 85.7%. Results from the classification showed 13 ha (33 ac) were dominated by medusahead.

4.2. Predicting Fractional Cover

4.2.1. Site S

Results from initial trials showed Random Forest, Cubist and Stochastic Gradient Boosting producing models of similar accuracies, all of which outperformed any of the

CART models (Fig. 3.1a). The final model was analyzed using 9,475 fCover pixels that were subset from 35,678 pixels that were available at Site S. From this dataset, 5% (n=475) were set aside for an independent test leaving 9,000 pixels to train the model. Using CVs, the final tuning parameters that produced the optimal performance were 400 trees, a shrinkage value of 0.05, and an interaction depth of 11 (Fig. 3.1b). The 10-fold CV of the final model produced an average RMSE of 13.9 and R^2 of 0.802 (n=9,000). The model was applied to all non-training pixels to produce fCover predictions for the entire site. This allowed for an independent validation which showed a RMSE 13.9 and a R^2 of 0.801 at $p < 0.01$ (n=475) (Fig. 3.2).

4.2.2. Sites C and N

To measure the predictive performance away from the training site, the observed and predicted fCover values at Sites C and N were evaluated using linear regression. Every observed fCover pixel available was used to evaluate the model at both sites. The performances at these sites were lower than Site S. Results for Site C showed a RMSE of 15.6 and a R^2 of 0.625; $p < 0.01$ (n=1,003) (Fig. 3.2). Site N resulted in a RMSE of 14.3 and a R^2 of 0.727; $p < 0.01$ (n=739) (Fig. 3.2). Based on these results, the two sites away of the training area averaged a RMSE of 14.95 and a R^2 0.676.

4.3. Visual Inspection of Outputs

This research was successful in integrating field collected data, high-resolution imagery and a coarser-resolution imagery for mapping medusahead distributions. Both the classification and prediction outputs provided good representations of what was observed in the field. Fractional cover analysis and RT modeling was successful at translating High-resolution classifications to Course-resolution prediction estimates and then used to develop a model that could delineate medusahead from cheatgrass (Fig. 3.3; Fig. 3.4).

The final model produced an output that characterized the 37,178 hectares (91,868 ac) within the study area into fCover values from 0-100% which allowed for a visual representation of highly impacted areas (Fig. 3.5).

5. DISCUSSION

5.1. Field Sampling

The protocol used in the field sampling strived to incorporate variations in rangeland components. Efforts need to be made to geo-reference only areas of homogeneous components, to minimize model confusion, but also need to include as much variation of different rangeland components as possible. The continuously collected field polygons proved to be a useful way to identify how different components were visually represented on the NAIP image.

5.2. Supervised Classification

The 1-meter resolution offered a reasonable resolution for reliable identification of medusahead monocultures. It became apparent that densely-populated medusahead produced a particularly unique visual representation on the NAIP imagery throughout the study area. In its senesced form, medusahead tended to reflect a bright yellow/white signature that aided in its identification on the NAIP image. This signature along with a unique matted texture were characteristics that led to the identification of areas of values to be extracted for the classification software.

One caveat of classifications is that it is unknown what gradient or threshold is the divergent point of the software classifying into either one class or the other. This can result in underpredictions for areas that do not meet the threshold to be classified as medusahead. For example, if the threshold of medusahead in the field was 50% for a pixel to be classified as present. Then a value of 49% would classify that pixel in the absent class and would cause an underprediction of medusahead.

Although accuracies for all sites fell within what is generally reported for classifications (60-90%) (Peterson, 2005), Site N showed a high Type II error by failing to detect medusahead at 25.0% of the locations. One hypothesis for this outcome is that the spectral characteristics were not as predominant in some of the recorded locations. During the field sampling stage at site N, it was observed that although medusahead was still a dominant vegetation type, most medusahead plants occurred shorter and in relatively sparser distributions compared to the other two sites. Jiapaer et al. (2011) found that sparsely distributed vegetation tends to exhibit weak spectral reflectance due to background interference. It would be fair to state that Site N would have had the highest probability, of the three sites, that the user recorded sparsely distributed patches as monocultures; this would have led to a weak signature of medusahead of that associated pixel and thus prevented the correct acquisition by the classification software.

5.3. Predicting Fractional Cover

The multi-scaled approach in this study provides a method to incorporate High-resolution classifications and Coarser-resolution spectral bands to be used to model and generate predictions of fractional estimates of medusahead. Translating the classification output to the Landsat image allowed for a greater number of spectral bands to be used to create predictor variables. The predictor variables for this study provided ample data to be “mined” by RT algorithms to successfully identify relationships with fCover values. Ultimately, the Stochastic Gradient Boosting algorithm was chosen over the other three RTs (CART, Random Forest, Cubist) to continue the modeling analysis with. This decision was influenced by characteristics of improved performance, robustness, and flexibility from the tuning parameters (Friedman, 2002; Elith et al., 2008; Kuhn & Johnson, 2013).

A challenge of modeling rangeland components, such as medusahead, is to incorporate training data that is robust enough to make accurate predictions across the landscape (Homer et al., 2012). The initial models were developed using varying number of training pixels. The optimum number of pixels were evaluated by 1) prediction accuracies and 2) computational intensities. This study found that a training set of roughly 10,000 training pixels provided prediction models that best minimized errors. Having a large population of data allowed for the ability to incorporate additional training data along the continuous gradient (0-100%) that show weak prediction performance. This proved to be beneficial in increasing the predictive performance throughout the range of continuous values. Incorporating additional training data to “boost” the performance of a specific range of predictions would have an impact on the internal 10-

fold CVs but it would not affect the results of the independent validations that were ultimately reported and used to validate the performance of the model.

Site S has approximately 187 ha (462 ac) of CRP land. The CRP is a voluntary USDA program that makes rental payments to owners in exchange for removing sensitive areas from agricultural practices. These areas can be used to enhance wildlife habitat, protect drinking water, and prevent soil erosion. The CRP land was observed to be heavily dominated by tall perennial and wheatgrass species [*Agropyron cristatum* (L.) Gaertn], [*Thinopryum ponticum* (Podp.) Z.-W. Liu & R.-C. Wang]) [*Leymus cinereus* (Scribner & Merrill) A. Löve]. Medusahead was noticed to be almost none existent in most of this area (see Fig. 3.5). Although there is a change in soil type from Benge gravel silt loam to Benge silt loam, Walla Walla silt loam, and Beckley coarse sandy loam (USDA-Soil Survey Geographic Database (SSURGO)) for large portions of the CRP, the distinct change in medusahead cover, seen in Fig. 3.5, generally follows the CRP's outer extent fence line. A potential reason for the medusahead not being dominant in this area was described in Davies & Sheley (2007b) and Sheley et al. (2008) in which the authors discuss that healthy perennial systems can resist and provide protection from invasion by medusahead. In addition, increased competition from perennial grasses reduces the spread of weedy and invasive species like medusahead (Blumenthal et al., 2003; Baker & Wilson, 2004; James, 2008).

The model at Sites C and N performed slightly below the training site at Site S. Although all the sites had respectable accuracies, one potential solution to increase the performance at these sites would have been the incorporation of training data from each of the other two sites. This would potentially increase the robustness of the model and result in better predictive performance at these sites. This was not done because this study was interested in evaluating the predictive performance away from the training site. During extrapolation, when the model encounters unfamiliar values, potential prediction errors could occur. This is believed to be what caused a potential overestimation of a 61 ha (150 ac) treated plot in the study area. During the *3.1. Field Sampling* protocol, the plot was observed to be heavily dominated by mustard (*Brassicaceae)* skeletons that formed a canopy over medusahead plants and recently established species ([*Agropyron cristatum* (L.) Gaertn]; [*Bassia prostrata* (L.) A.J. Scott]) which were drilled for revegetation. During the time of analysis, the plot was in the middle stage of a two-year USDA reclamation project, which was being treated due to the medusahead invasion (C. Stonecipher & K. Panter, personal communication, October 29, 2015). The plot was not within any of the three study sites, so no field data was collected within the plot. The potential error became apparent during a visual inspection of a prediction output. The plot "stands out" due to its anthropogenic shape and dissimilarity which is pointed out in Fig. 3.5. Although this is believed to be a minor component on heterogenous rangelands, it is important to point out an error of the model in miss-predicting mustard skeletons where they are abundant. Areas of agriculture and urban developments would represent spectral values that would not have been input into the model via the training data and can cause false predictions. Efforts were made to remove these areas from analysis, but another potential source of error would be any area that should have been removed but was missed.

5.4. Other Considerations

This study was successful at modeling and predicting medusahead which was discriminated from cheatgrass. Fig. 3.4 shows an area next to an agricultural field that was observed to be densely dominated by cheatgrass (dark brown) with the road, pockets and surrounding areas being dominated by medusahead. The prediction output shows relatively low amounts of medusahead estimated in most of the area dominated by cheatgrass. For this delineation to be possible, it is imperative that the classifications make this distinction, so they can be used to train the model. Separation of these two species at the landscape level should prove to be valuable to land managers tasked with controlling and abating weed invasions and allocating necessary treatments. Although not tested, it is believed that other rangeland components, derived from the classifications, show promise in similar mapping methods. One component of interest would be cheatgrass.

Prediction errors are inevitable but one way to limit the amount of error would be to limit the output of analysis to areas that have been or have a high probability of invasion from medusahead. One way to implement such approach would be to use the phenology-driven method in conjunction with the multi-scaled approach described in this research. This would potentially limit the predictions to areas dominated by annuals.

This research showed an ability to quantify, model, and predict medusahead using dense populations as training data. It appears that sparsely distributed medusahead plants could be overshadowed by background spectral signatures. Thus, a limitation of this method would be detecting areas of single or loosely populated plants. Although it has some limitations, an ability to map dense populations should prove to be useful for land managers interested in exploring and better understanding both the spatial and temporal dynamics of medusahead so novel or improve management plans can be produced. Continued research in exploring the spatial and temporal dynamics are ongoing and will be reported in ensuing chapters.

6. CONCLUSION

This research offers an advancement for predicting fractional estimates of invasive annual grasses across western rangelands. Using spectral characteristics, this study demonstrates an ability to delineate senesced medusahead monocultures from other rangeland components and accurately predict their distributions.

Without successful management, education, and changes in behavior, medusahead will continue to invade United States western rangelands. The results from this study demonstrate the predictive ability of RT algorithms for rangeland components including medusahead. Large-scale mapping of medusahead may allow managers to gain a better understanding of the dispersal characteristics of the species that should aid in protecting and rehabilitating rangelands. This research should offer opportunities and progression in the development of novel or improved management approaches, leading to more adaptable and sustainable programs aimed at managing rangelands challenged by medusahead invasion.

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TABLES AND FIGURES

Table 3.1
Ratio and combination indices that were used to make relationships and develop the prediction model.

Name	Equation	Reference
NDVI	$\boldsymbol{NDVI} = \frac{NIR - RED}{NIR + RED}$	Rouse et al. (1973)
DVI	$\boldsymbol{DVI} = NIR - RED$	Tucker (1980)
GNDVI	$\boldsymbol{GNDVI} = \frac{NIR - GREEN}{NIR + GREEN}$	Gitelson et al. (1996)
GDVI	$\boldsymbol{GDVI} = NIR - GREEN$	Sripada et al. (2006) Tucker (1979)
RDVI	$\boldsymbol{RDVI} = \frac{NIR - RED}{\sqrt{NIR + RED}}$	Rougean & Breon (1995)
RVI	$\boldsymbol{RVI} = \frac{NIR}{RED}$	Huete and Jackson (1987)
Norm G	$\boldsymbol{NG} = \frac{GREEN}{(NIR + GREEN + RED)}$	Sripada et al. (2006)
Norm R	$\boldsymbol{NR} = \frac{RED}{(NIR + GREEN + RED)}$	Sripada et al. (2006)
Norm NIR	$\boldsymbol{NNIR} = \frac{NIR}{(NIR + GREEN + RED)}$	Sripada et al. (2006)
SLAVI	$\boldsymbol{SLAVI} = \frac{NIR}{RED + SWIR_7}$	Lymburner et al. (2000)
GIPVI	$\boldsymbol{GIPVI} = \frac{NIR}{NIR + GREEN}$	Maseola er al. (2016)
NDII5	$\boldsymbol{NDII5} = \frac{NIR - SWIR_5}{NIR + SWIR_5}$	Wilson et al. (2016)
NDII7	$\boldsymbol{NDII7} = \frac{NIR - SWIR_7}{NIR + SWIR_7}$	Wilson et al. (2016)
NDSVI	$\boldsymbol{NDSVI} = \frac{SWIR_5 - RED}{SWIR_5 + RED}$	Qi et al. (2002)

NDTI	$\boldsymbol{NDTI} = \frac{SWIR_5 - SWIR_7}{SWIR_5 + SWIR_7}$	van Deventer et al. (1997)
MSI	$\boldsymbol{MSI} = \frac{SWIR_5}{RED}$	Harris et al. (2005)
$MSAVI_2$	$\boldsymbol{MSAVI_2} = \frac{2NIR + 1 - \sqrt{(2NIR + 1)^1 - 8(NIR - RED)}}{2}$	Qi et al. (1994)
OSAVI	$\boldsymbol{OSAVI} = \{\frac{(\boldsymbol{NIR_{RED}})}{(\boldsymbol{NIR+RED+L})}\} * (1 + L)$ *Where L=0.16*	Rondeaux et al. (1996)
SAVI	$\boldsymbol{SAVI} = \frac{(\boldsymbol{NIR_{RED}})*(\boldsymbol{1+L})}{(\boldsymbol{NIR+RED+L})}$ *Where L=0.5*	Huete (1988)
NDSI	$\boldsymbol{NDVI} = \frac{RED - NIR}{RED + NIR}$	Allbed & Kumar (2013)
SI	$\boldsymbol{SI} = \sqrt{BLUE * RED}$	Allbed & Kumar (2013)
RVI_1	$\boldsymbol{RVI_1} = \frac{RED}{NIR}$	ERDAS IMAGINE 16.00
VIS	$\boldsymbol{VIS} = BLUE + GREEN + RED$	-

Table 3.2
Confusion Matrix for the classification outputs for each site of the three sites.

	OBSERVED				
PREDICTED	**SITE S**				
	CLASS	Medusahead	Non-Medusahead	Total	Accuracy
	Medusahead	**24**	2	26	92.3%
	Non-Medusahead	1	**73**	74	98.6%
	Total	25	75	100	
	Accuracy	96.0%	97.3%		**97.0%**
	SITE C				
	Medusahead	**6**	0	6	100.0%
	Non-Medusahead	1	**7**	8	87.5%
	Total	7	7	14	
	Accuracy	85.7%	100.0%		**92.9%**
	SITE N				
	Medusahead	**6**	1	7	85.7%
	Non-Medusahead	2	**18**	20	90.0%
	Total	8	19	27	
	Accuracy	75.0%	94.7%		**88.9%**

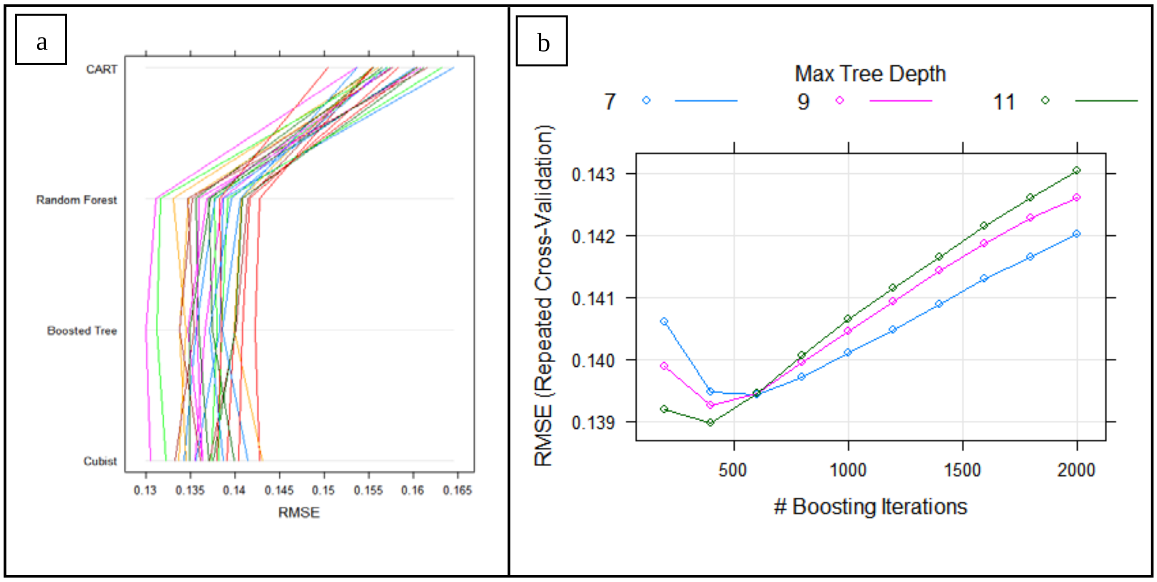

Fig. 3.1. Performance of the regression tree algorithms and the performance of the Stochastic Gradient Boosting tuning parameter.

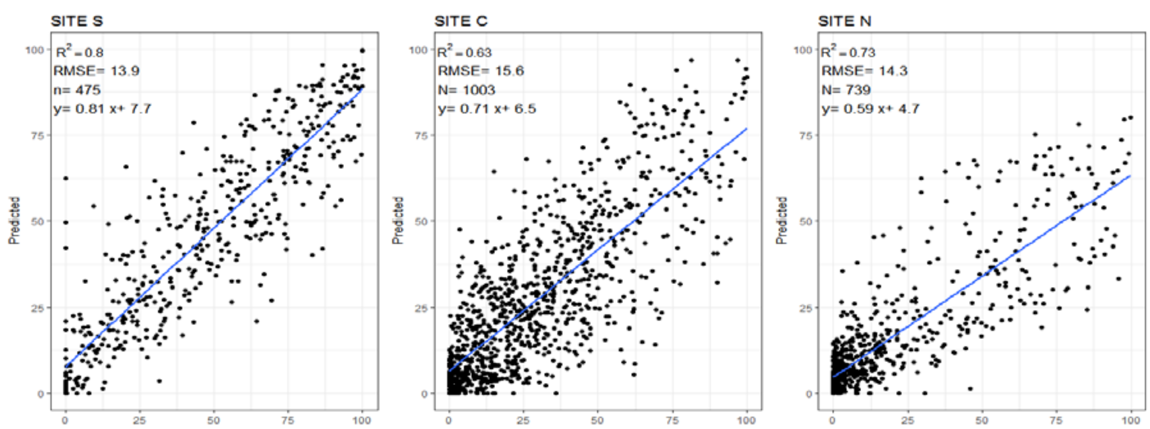

Fig. 3.2. Results of the independent tests used to measure the predictive performance of the 2015 model near (Site S) and away (Sites N and C) from the training location.

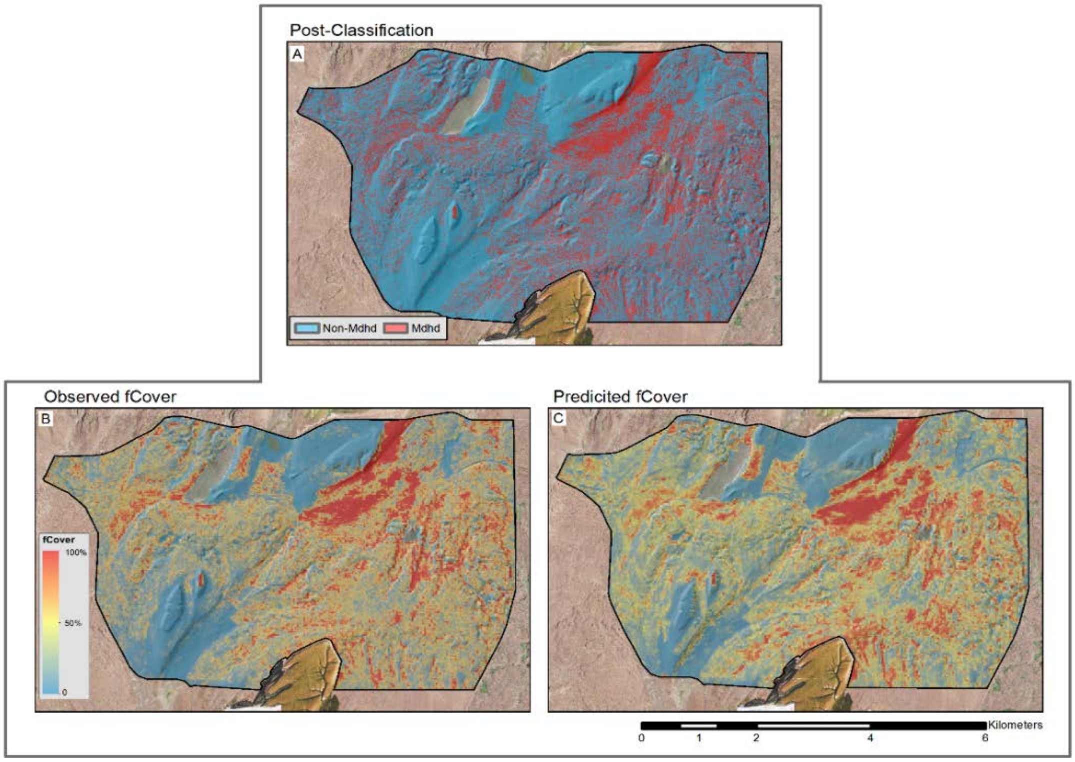

Fig. 3.3. Images of the classification output (A), the created fCover (B), and the predicted fCover at Site S (C).

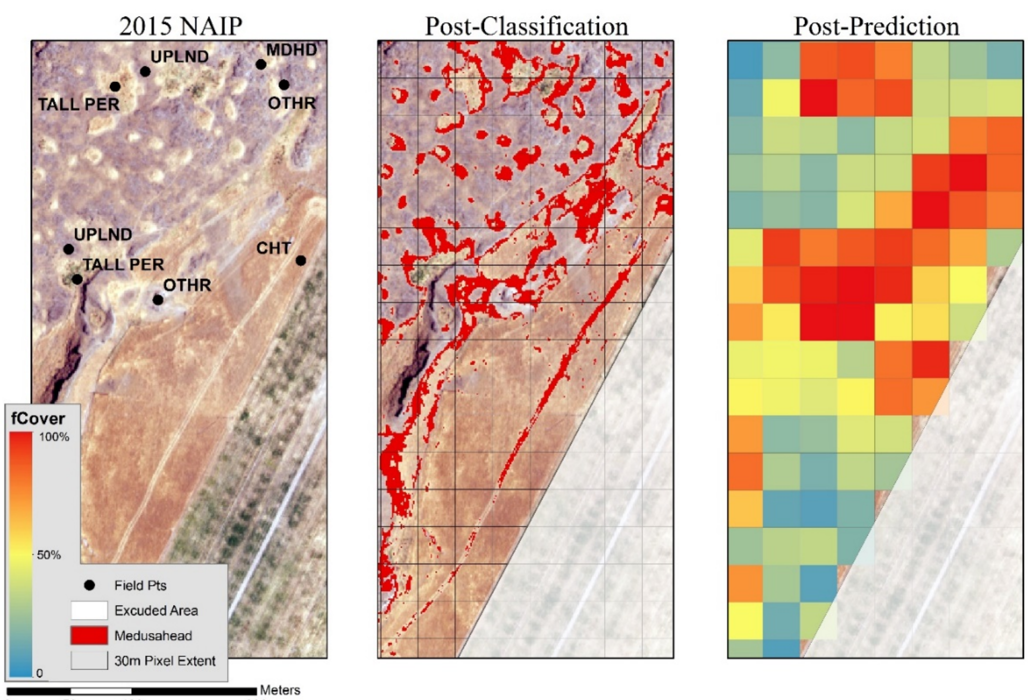

Fig. 3.4. Collected field points, classification output, and prediction output. Shows the models ability to delineate cheatgrass (dark brown) from medusahead.

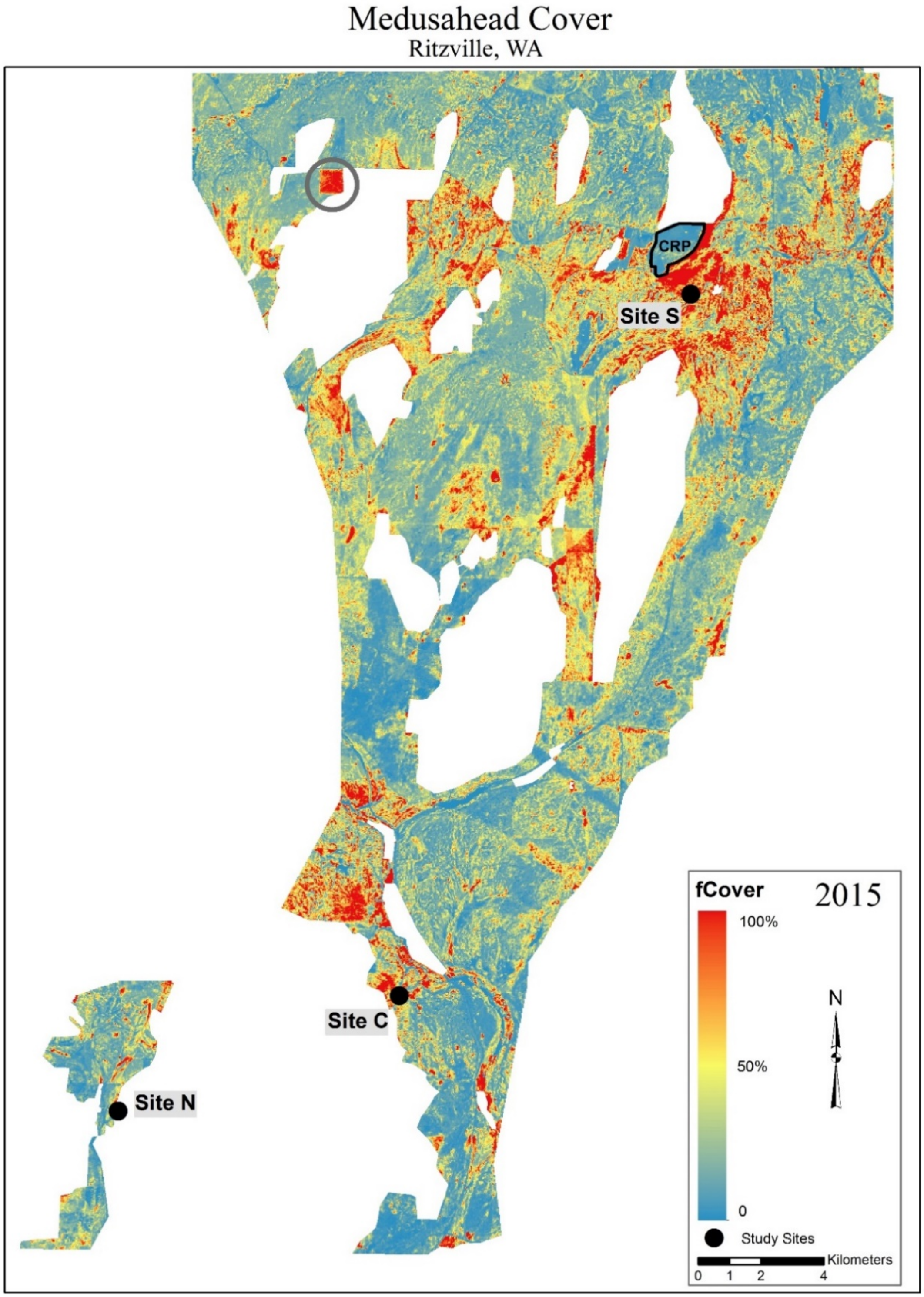

Fig. 3.5. Prediction output of fCover for the study area for 2015. Circled area represents possible over-prediction due to mustard skeletons.

CHAPTER 4

TIME SERIES ANALYSIS OF MEDUSHEAD (*Taeniatherum caput-medusae*) DISTIBUTIONS IN THE CHANNELED SCABLANDS OF EASTERN WASHINGTON USING PREDICTIVE MODELING OF REMOTELY SENSED IMAGERY

ABSTRACT

Measuring ecological changes and detecting trends through time can aid managers in making informed decisions about controlling invasive species in threatened landscapes. Traditional, ground-based methods that detect changes through time may present delayed results that miss important variables outside of a sample plot. Time series analysis, using remote sensing techniques and archived imagery, can produce significant landscape-level results in a relatively quick and cost-efficient manner. This study was conducted to explore the practicality of remote sensing time series analysis by ascertaining information on the historic temporal dynamics and trends of medusahead (*Taeniatherum caput-medusae* [L.] Nevski) cover within the Channeled Scablands region of eastern Washington. Using a multi-scaled approach, a 30+ year historic time line of medusahead cover was estimated by developing a Regression Tree model that made predictions based on unique spectral relationships of standardized Landsat scenes. The validity of the time line was supported from qualitative time line reports near the study area. The time line was analyzed to estimate a trend of mean cover and per-pixel trends with their associated magnitude of changes, from 1985 to 2016. Results showed a highly dynamic time line with fluctuations from “high” to “low medusahead cover” years with

peak “high” years increasing in magnitude with time. Although a significant trend of mean cover was not detected, the results of the per-pixel assessment characterized the landscape into areas of significant increasing/decreasing trends. This technique has the potential to help managers make quicker and regionally informed decisions aimed at improving the health of western rangelands challenged by medusahead invasion.

1. INTRODUCTION

Knowledge of temporal changes in ecological systems is an important endeavor in ecological research (Magurran et al., 2010). Traditional, ground-based methods typically include initial measurement collections compared to additional sequential measurements of the same location for a specified amount of time (Olsen et al., 1999; Magurran et al., 2010). These methods can have financial, spatial, and temporal limitations for researchers especially when measurements are needed at larger scale extents (Hunt et al., 2003; Kerr & Ostrovsky, 2003; Xian et al., 2015). Archived imagery and remote sensing techniques allows for rapid assessment of temporal changes that can provide immediate information of entire populations (Shuman & Ambrose, 2003; White et al., 2014; Yip et al., 2015). Providing more timely information to managers allow for quicker applications that can yield greater influences and benefits to rangeland systems. In the case of some measurement objectives, remote sensing can be a more efficient method or potentially provide the only means of measurements when compared to ground-based techniques (Kerr & Ostrovsky, 2003; Shuman & Ambrose, 2003

The Landsat satellite series offers more than 40 years of near-continuous, systematically collected imagery that make it valuable for time series and change detection analysis (Chander et al., 2009). Publicly available, multi-temporal Landsat scenes have been used to detect and predict land cover changes in both forest and rangeland systems (Rivera et al., 2011; Vogelmann et al., 2012; Zhu & Woodcock, 2014). The ability to examine past land cover changes can allow managers to be proactive while assessing future changes and identifing vital clues into troubled systems. Compared to the time limitations of traditional - future-based - change detection methods, assessment of past changes can provide immediate information to decision makers regarding the ecological health of a certain area in a natural or productive landscape. This in turn can provide valuable additional time so new polices and management actions can be implemented with the greatest influences and benefits to the ecosystems under study. Nevertheless, remote sensing-based time series analysis may not be as straightforward as many researchers may hope. Individual images may differ greatly due to changes in vegetation and land cover and may be influenced differently by atmospheric and sensor effects which tend to change with time (Yang & Lo, 2000; Chander et al., 2009). To maximize the benefit of change detection being related to actual on the ground changes, researchers need to take steps to account for unwanted variations and use standardization methods to account for phenological and land cover changes, atmospheric noise and sensor deterioration over time (Chávez, 1996; Homer et al., 2012; Carvalho et al., 2013).

Time series analysis of invasive species, using remote sensing methodologies, can lead to a better understanding of dispersal characteristics, and improve distribution models (Rocchini et al., 2015). Researchers have used, sometimes through interpolation, continuous time-series datasets to map and estimate the changing abundance of cheatgrass (*Bromus tectorum*) over large extents of the western United States (Clinton et al., 2010; Boyte et al., 2015). Research like this, has the potential to play vital roles in the management of detrimental weedy species in arid rangelands by allowing managers to prioritize and direct management resources in more efficient and effective ways.

Medusahead (*Taeniatherum caput-medusae* [L.] Nevski) is an aggressive annual that has become a pressing problem in western rangelands and areas of agriculture. Medusahead has invaded almost 1 million ha of rangeland in the western United States (Duncan et al., 2004; Rice, 2005). Medusahead is degrading rangelands through significant reductions in biodiversity and has reduced primary productivity by as much as 90% (Hironaka, 1961; Davies & Svejcar, 2008). Like many annuals, medusahead is a prolific seed producer that displays phenological traits of early green-up in the spring and senescence early into the growing season (Young, 1992; Kyser et al., 2014; Nafus & Davies, 2014). Conducting temporal analysis of invasive species, like medusahead, at a landscape level could provide information that would aid in developing and improving preventative efforts that would prove to be more cost-effective than eradication and rehabilitation efforts of sites that are already invaded (DiTomaso, 2000; Davies, 2008). This information could be directly translated into effective and efficient methodologies that would assist land managers struggling with the invasion.

In Chapter 2 it was reported that Regression Tree (RT) algorithms, used to model spectral relationships, can accurately predict continuous cover estimates of medusahead across large portions of rangelands. The purpose of this Chapter is to explore the possibility of acquiring information about the temporal dynamics of medusahead in the Channeled Scabland region of eastern Washington. A hypothesis was developed that if Landsat scenes could be standardized for effects outside of on ground medusahead distributional shifts, then spectral signatures of medusahead from a time series dataset would be similar enough for annual predictions to be made from a single year's prediction model. Thus, the objectives for this study are to: 1) create and standardize a continuous time series of annual Landsat scenes (1985-2016); 2) develop a single scene prediction model; 3) reapply the model to individual scenes to create a time series dataset of annual predictions; and finally, 4) estimate trends and magnitude of changes for the study area.

2. STUDY AREA

The study was conducted within the Channeled Scabland region of eastern Washington and consisted of 37,178 hectares (91,868 ac) of rangelands southeast of Ritzville, WA (46°48.23'N, 118° 16.98'W; 434 m). The vegetation community was once categorized as steppe and shrub-steppe with climax communities being dominated by *Artemisia tripartita*, *Agropyron spicatum* and *Festuca idahoensis* (Daubenmire, 1970; Franklin & Dyrness, 1973) but is now dominated by annual grasses, such as cheatgrass; medusahead; and weedy forbs fiddleneck (*Amsinckia intermedia* Fisch. & Mey), tansy mustard [*Descurainia pinnata* (Walt.) Britt.], rush skeletonweed (*Chondrilla juncea* L.), black mustard [*Brassica nigra* (L.) Koch in Roehl], and filaree [*Erodium cicutarium* (L.) L'Hér.] (Ralphs et al., 2011b). Areas with wheatgrass species ([*Pseudoroegneria spicata* (Pursh) A. Löve], [*Agropyron cristatum* (L.) Gaertn], [*Thinopryum ponticum* (Podp.) Z.-W. Liu & R.-C. Wang]) and basin wildrye [*Leymus cinereus* (Scribner & Merrill) A. Löve] were present but were scarce.

The climate is semiarid with a 50-year average annual precipitation of 272 mm (NOAA, 2017). The elevation slopes from the north to south and ranges from 600m to 323m. Large elevated areas, which are generally 45-75m above the surrounding rangelands, tend to increase in frequency moving further south. The tops of these areas have deep, high-quality soils and are typically used for agricultural production, while the surrounding areas are generally used for grazing livestock and are scattered with agriculture and urban developments.

Extensive grazing and repeated fires have led to many areas becoming dominated by annual invasive species (Daubenmire, 1970; West & Young, 2000). Today, the competitive ability of medusahead has displaced many areas once dominated by cheatgrass which has led to medusahead becoming the dominant player in large portions of eastern Washington (Hironaka, 1994). Since the 2000s, herd sizes in the area have been reduced in some cases by 50% and producers have had to change practices to mitigate losses from the invasion of medusahead. These changes include: adding additional farming operations, altering historic grazing practices, modifying calving strategies, and increasing supplemental forage (Information gathered by interactions with producers from the region).

2.1. Site Descriptions

The model development process took place at three sites spanning over a 33 km transect. This was done to take advantage of any variations in rangeland conditions and environmental factors while providing independent test sites for the prediction model. Site S, located about 26 km southeast of Ritzville, WA (47°03.16’N, 118°02.79’W, 553 m), consisted of approximately 3,209 ha (7,930 ac) of grazed rangelands with roughly 187 ha (462 ac) being used in the United States Department of Agriculture (USDA) Conservation Reserve Program **(**CRP). The CRP portion of the site was heavily dominated by tall perennial and wheatgrass species [*Agropyron cristatum* (L.) Gaertn], [*Thinopryum ponticum* (Podp.) Z.-W. Liu & R.-C. Wang]) [*Leymus cinereus* (Scribner & Merrill) A. Löve]. The soil taxonomy falls into the categories of Benge gravelly silt loam and Loamy to Coarse-loamy, mixed, superactive, mesic typic and lithic haploxerolls (Anders-Kuhl extremely rocky silt loams). Site C, located about 26 km south of Site S (46°50.29'N, 118°09.99'W, 469 m, consisted of approximately 60 ha (148 ac) of grazed rangeland. The soil classification is the same as Site S (Benge gravelly silt loam). Site N, located 33 km south southwest of Site S (46°48.23'N, 118° 16.98'W, 434 m), consisted of approximately 73 ha (181 ac). The soil taxonomic class is a coarse-loamy over sandy or sandy skeletal, mixed, superactive, mesic calcidic haploxeroll (Stratford silt loam).

3. MATERIALS AND METHODS

This research was interested in estimating a 30+ year time line of annual medusahead cover from which any trends and magnitude of changes in the area could be identified. This was done by developing a single scene validated prediction model and then reapplying the model to individual scenes of a standardized Landsat time series. The time series predictions were restricted to areas outside of agricultural areas, urban developments and steep elevation changes.

3.1. Model and Time Series Development

Annual Landsat Thematic Mapper (TM) and Operational Land Imager (OLI) scenes were used to generate the time series from years 1985-2016. Scenes from Path43;44/Row27 were downloaded from the United States Geological Survey-Earth Explorer website (USDI-USGS, 2016). Each scene must have been acquisitioned within ± 3 weeks of August 05 to be used in the time series. This limitation aided in minimizing phenological differences between individual images. The images were projected to the UTM zone 11 NAD83 coordinate system, clipped, rescaled to TOA percent reflectance (Chander et al., 2009; Landsat, 2016), normalized for sun angle, and normalized to a single reference scene, using Pseudo-invariant Features (PIF) (Schott et al., 1988). The reference scene was identified by assessing the dynamic range of digital numbers from scenes closest to the median of the time sequence (Yang & Lo, 2000). The reference scene was chosen by selecting the scene with the largest range of digital number values within ± 3 scenes from the median scene of the time sequence. This was done to help minimize false land cover changes between the subject and reference image while maintaining as much pixel information as possible (Yang & Lo, 2000).

Once the Landsat scenes were normalized and standardized, a prediction model was developed using the 2015 image. This was done using the same methods, dependent dataset (fCover), and predictor variables (derived from TM bands 1,2,3,4,5,7 & OLI bands 2,3,4,5,6,7) outlined in Chapter 2. Identifying an appropriate accuracy threshold was done by assessing R^2 values from past research predicting similar rangeland components (Peterson, 2005; Sant et al., 2014; Xian et al., 2015). The threshold of a $R^2 > 0.75$ for the independent test at Site S was used to characterize an acceptable prediction performance. Once a model's performance was deemed acceptable, it was applied to the predictor (independent) variables of each year. This created a dataset of annual fCover estimates for each year of the time series.

3.2. Time Series Analysis of the Study Area

This study wanted to identify any potential trends in medusahead cover and, if present, the magnitude of change of medusahead cover in the time series. The mean fCover values of the study area were used for the time series analysis. Mean values were chosen because of the skewed distribution of values caused by the large amount of zero and near-zero predictions. It was found that median values would have failed to detect most annual estimates due to the high amount of zero medusahead cover estimates.

Interpolation was used to account for missing values due to Landsat years that were either unavailable or did not meet the above-mentioned stipulations. Cubic hermites (splines) were applied on a per pixel basis to create raster layers representing missing years. These layers were added to the time series to create a continuous dataset from years 1985-2016. Splines were selected because they have shown to be an adequate way to interpolate non-smoothed data (Fritsch & Carlson, 1980; Martinez & Gilabert, 2009) and have been used to estimate missing remote sensing data (Clinton et al., 2010).

The mean fCover values for the study area were assessed to identify potential trends and magnitude of change. The Mann-Kendall test was used to test the significance of any trend while the magnitude of change was characterized by a slope estimate found using ordinary least squares (OLS). The Mann-Kendall is a non-parametric test that has become popular in remote sensing, time series applications because it's less sensitive to outliers and it has relaxed assumptions compared to parametric tests (Martinez & Gilabert, 2009; Jong et al., 2011; Forkel et al., 2013). The test identifies monotonic trends that are statistically different from zero, under the assumptions of an identically distributed and non-serially correlated dataset (Mann, 1945; Kendall, 1975, Hamed, 2008). To assure the assumptions were met, the data was tested for serial correlation by using an autocorrelation test (Venables & Ripley, 2002).

3.3. Time Series Analysis Per Pixel

This study wanted to identify any location (pixel time series) showing an increasing/decreasing trend in medusahead cover and then estimate the rate of change. This was done by applying the Mann-Kendall test and OLS to annual fCover values for each pixel in the study area going through time. Serially-correlated data can be common in natural systems and can cause an increase chance of false detection of trends (Type I error) (Bayazit & Önöz, 2007). To account for this in the dataset, the Zhang pre-whitening method was used which validates series by detrending any series suggesting a trend until correlation is minimal (Zhang et al., 2000). Although pre-whitening a dataset does present a risk of not detecting trends when trends due exists (Type II error), it has been suggested that pre-whitening short series ($n \leq 50$) outweighs this potential cost and should be conducted (Yue & Wang, 2002; Bayazit & Önöz, 2004; Bayazit & Önöz, 2007). The magnitude of change and direction (increasing/decreasing) of a trend was characterized by an estimation of slope from OLS.

3.4. Accuracy Assessment

3.4.1. Prediction Model Assessment

The metrics used to evaluate prediction performances were Root Mean Squared Error (RMSE) and the correlation determination (R^2). The RMSE is a measurement of the variance between the predicted and observed values and is reported in the same unit as the modeled variable. The R^2 is a number representing a measurement of the amount of total variation that can be explained by the model (0, no variation explained; 1, all variation explained). Both metrics have been used in ecological remote sensing research as a measurement of prediction performance (Homer et al., 2013; Xian et al., 2013; Boyte et al., 2015). The model was evaluated using independent tests at the three sites following methods outlined in Chapter 2. The prediction metrics were found by regressing predicted and withheld fCover values using the R environment (R Development Core Team, 2016). For an accuracy assessment, 5% of the sample pixels from Site S were withheld and all the pixels available from Sites C & N were withheld for these tests. The test at Site S was used to assess the model's performance near the training site while the tests at Sites C & N were used to evaluate the performance away from the training site (26km; 33km, respectively).

3.4.2. Temporal Assessment

Assessing the accuracy of the predicted time series dataset was difficult because we did not have any collected data to reference prior to year 2015. To overcome this, we gathered qualitative reports and accounts from the area for the purpose of gaining an understanding of the time line of the medusahead invasion in the area. This research reached out to federal and state agencies, conducted literature reviews, and developed a questionnaire requesting information from individuals who were familiar with the area through the targeted period. The questionnaire strived to identify 1) when the participant first noticed medusahead, 2) if there was a time medusahead was noticed to be increasing, and 3) when did medusahead become dominate in area. The questionnaire requested either a specific year or a period of years from the participant (1985-1990; late 90's etc.).

4. RESULTS

4.1. Model and Time Series Development

After assessing the Landsat scenes for the area, 29 of the 32 years were available and met the stipulations mentioned in the *Model and Time Series Development* section. The missing values of years 1987,1993 and 2012 were estimated from per pixel interpolation. The August 5th, 2001 TM scene showed the highest dynamic range in digital numbers and was selected as the master scene for the PIF process.

The model development process utilized 9750 randomly stratified fCover pixels from Site S and all available pixels at Sites C & N (1,003, 739, respectively). The independent test resulted in a RMSE 13.5 and a R^2 of 0.81 at Site S (n=489, $p < 0.01$), RMSE 17.0 and a R^2 of 0.68 at Site C (n=1,003, $p < 0.01$), and RMSE 14.7 and a R^2 of 0.72 at Site N (n=739, $p < 0.01$) (Fig. 4.1).

4.2. Time Series Analysis of the Study Area

Annual mean fCover values, for the study area, resulted in a dynamic time series with five major peaks that increased in magnitude with time (Fig. 4.2a). The Mann-

Kendall test failed to detect a significant trend ($\alpha \leq 0.05$) with a p-value of 0.355. The estimated slope from OLS was 0.146 but is viewed as irrelevant due to the failed Mann-Kendall test (Fig. 4.2b).

4.3. Time Series Analysis Per-Pixel

The Mann-Kendall test, at a significance level of ($\alpha \leq 0.05$), estimated 4,612 ha (11,397 ac) that showed an increasing trend and 164 ha (405 ac) that showed a decreasing trend for years 1985-2016 (Fig. 4.3)**.** The slope estimates, from OLS, ranged from -1.74 to 2.05%.

4.4. Temporal Assessment

Results from the literature review reported medusahead was present in eastern Washington as early as year 1901 at Steptoe Butte, 54 km east of the study area (McKell et al., 1962). By the 1960's and 1970's authors had characterized medusahead as being "widely distributed" in semi-arid regions of southeastern Washington and entering steppe regions near the study area. Although, most of the emphasis was on other invasive species like cheatgrass (*Bromus tectorum*) and Kentucky bluegrass (*Poa pratensis*) (McKell et al., 1962; Daubenmire, 1970; Franklin & Dryness, 1973). Medusahead was listed as a Class B (distribution is limited to portions of Washington) noxious weed on Washington State's Noxious Weed Control Board in years 1988 and 1989 (WS, 2017). Ralphs et al. (2006) conducted research in the area on velvet lupine (*Lupinus leucophyllus*) in years 2001, 2002, and 2003 in which the authors list a number annual species degrading the area but there is no specific reference of medusahead. Two similar studies were conducted in the same area from years 2002-2009 and 2007-2008 in which the authors stated medusahead was co-dominating the area with cheatgrass (Ralphs et al., 2011a; Ralphs et al., 2011b). From years 2011-2014 two studies aimed at mitigation and revegetation of medusahead invaded areas, were conducted within the study area, in which medusahead is stated to have been a major vegetation component to area (Stonecipher et al., 2016; Stonecipher et al., 2017). Finally, in 2016 Medusahead was listed as a Class C (distribution is widespread in Washington and of special interest to the agricultural industry) noxious weed on Washington States Noxious Weed Board (WS, 2017).

Four individuals responded to the questionnaire and provided their accounts of the time line of the medusahead invasion in the area. The participants included, two livestock producers that lived within the study area and two Washington State weed specialists who were familiar with eastern Adams County, WA. The response from one of the weed specialist was removed due to the limited period that the individual had worked in the area. The responses from the questionnaire seemingly show a strong agreement among the three participants; medusahead was first noticed in the early-mid 1990’s and medusahead became dominant by the early-mid 2000’s (Table 4.1).

5. DISCUSSION

5.1. Model and Time Series Development

As discussed in Chapter 2, a challenge of modeling rangeland components is to incorporate training data that is robust enough to make accurate predictions across the landscape (Homer et al., 2012). The decrease in prediction performance away from the training area is believed to be due to variations of land cover signatures that were not included as training data. Although it is beyond the scope of this research, efforts could be made to include training data from areas outside of Site S which could potentially increase the prediction performance at Sites C and N.

5.2. Time Series Analysis of the Study Area

Results from the time series analysis, of the study area, showed steep fluctuations of mean fCover estimates through the time. This included peak years that recurred from four to eight years which tended to increase in magnitude. The year predicting the largest mean fCover value (2015) does coincide with the 2015 NAIP & 2015 Landsat used to develop the prediction model. It is possible that developing the prediction model from these images may be an underlying cause of estimating the highest annual value seen in Fig. 4.2a. Although, the general behavior of the peaks increasing in magnitude through the time series can be viewed as support for this large peak.

A potential explanation for the fluctuating behavior, seen in in Fig. 4.2a, might have to do with typical temporal dynamics of annual species. The fluctuations of mean fCover values would be consistent behavior of what would be expect of an annual species which begin from seed each year. As an annual, seedling performance and the competitive advantage of medusahead can be dependent on year-to-year resource availability and environmental conditions whereas the more resilient perennial plants can rely on stored resources and access to large volumes of soil (James et al., 2011; Leffler et al., 2011). Also, medusahead seeds can remain dormant for up to three years which can then germinate when conditions are more favorable leading to single year flushes of the plant (Young & Evans, 1970; Young et al., 1998; Nafus & Davies, 2014). Certain conditions allowing for dominant and less dominant years of medusahead, may be influencing the temporal dynamics seen in the time series dataset. Some of these potential conditions are explored in the final chapter of this thesis.

A second potential explanation for the varying behavior came upon re-visiting the study area, for an unrelated project, in fall of 2016 and summer of 2017. The increases and decreases in mean fCover may be explained by the spectral signatures, used by the prediction model, being “drowned out” by stronger background or foreground signatures. The large dense patches, noted in 2015, were less frequent with majority of the medusahead plants occurring in relatively sparser distributions compared to 2015. Jiapaer et al. (2011) discussed that low densities of target vegetation can produce weaker signatures that could be drowned out by background signatures, allowing for a species to go undetected. In addition to the lower density of medusahead, the vegetation community was different compared to 2015. While investigating the dramatic drop in fCover from 2015 to 2106, large portions of the study area were found to produce high Infrared Red (IR) values on the August 2016 Landsat 8 image. The reason for this was explained by a large abundance of green Rush Skeleton weed (*Chondrilla juncea* L.) that grew above much of the medusahead in the area. Rush Skeleton weed can remain in a photosynthetic state well into the fall (Sheley et al., 1999; Whitson et al., 2012), which produced the high IR readings on the August image. This type of situation, like what was discussed in Jiapaer et al. (2011), probably produced foreground signatures that allowed medusahead to go undetected and probably produced underpredictions for the year 2016. The potential of this type of error occurring throughout the time series was acknowledged during the design of this study. This study’s attempt to minimize year to year phenological differences was to use near August imagery, when majority of the vegetation had senesced or gone dormant. The use of even later imagery was assessed but was decided against due to the decrease in the number of cloud-free images. These types of situations (strong background and foreground signatures) may be contributing factors causing the sharp inclines and declines seen in Fig. 4.2a. Although steps were taken to delineate and describe actual temporal changes in medusahead cover, it is impossible to account for every anomaly.

The Mann Kendall test failed to detect any significant trend of mean fCover values from 1985-2016 Fig. 4.2b. From literature and reported accounts, it is known that medusahead has been increasing in the area for the last 100+ years. This would suggest that an increasing trend of medusahead should have been detected. A hypothesis of why there was a failure to detect a significant trend might be related to three factors: 1) Using a mean value for the entire study area may have “diluted” many of the year-to-year changes; 2) Situations that caused weak signatures may have caused lower or missed predictions; 3) The small sample size (n=32) does not allow for enough observations for the changes to be significant.

5.3. Temporal Assessment

Although post hoc time series results can be difficult to validate, the steps taken to assemble past information has allowed for a reliable time line of the medusahead invasion in the area. This time line is characterized from the results of the qualitative assessment and suggest: 1) medusahead probably had been in the area earlier than the initial year of the time series (1985), 2) the plant seems to have spread enough through the state of Washington to cause it to be listed as a noxious weed in 1988-1989, 3) individuals familiar with the study area only began to notice medusahead by the early-mid 1990s, 4) medusahead continues to spread until it is a dominant or codominant species through the 2000's, and 5) by early-mid 2010s medusahead in the area is widespread and of major concern for the agricultural industry.

Findings from the qualitative assessment seem to show some support for the results from the temporal assessment of the time series data. The first peak in Fig. 4.2a corresponds around the period when medusahead was initially listed as a noxious weed (1988-1989) as well as a period when individuals from the questionnaire began noticing medusahead in the area (early to mid-1990s) (Table 4.1). Although a more defendable correspondence might had been available had Landsat TM imagery been available prior to 1985. Additionally, there is a more noticeable increase in the magnitude of the peak at year 2003, compared to the two prior peaks at 1989 and 1996. The 2003 peak of mean fCover is consistent with literature (2000s) and the individual reports in Table 1 (early-mid 2000s) being the period when medusahead become a dominant or codominant species. From personal accounts, the 2000s were a period when producers in the area had to reduce herd sizes and take on additional or alternative activities (grazing and calving changes, farming, additional supplemental feed) to help mitigate costs of forage reduction. (Information gathered by interactions with producers from the region). Although beforehand data collection or a larger sample size would have produced a more defendable validation, results obtained from the time series analysis seem to agree with the time line that was identified from the literature and personal accounts from the study area.

5.4. Time Series Analysis Per-Pixel

The decision to pre-whiten the time series data was felt to be necessary due to the small sample size of years in the time series. Applying the Mann-Kendall test on a per pixel basis, classified the study area into areas of increasing, decreasing, non-significant trends. The per-pixel analysis displayed areas throughout the study area that showed different variations of increasing fCover estimates from 1985-2016. It is interesting to note that nearly the entire CRP portion of Site S has shown no trend of medusahead (see Fig. 4.3). The CRP was described in Chapter 2 as an area that may be able to resist invasion due to the different vegetative component present. The estimates of increasing, decreasing, and without trends, throughout the study area, may provide critical information to land managers about dispersal characteristics of medusahead in the area.

5.5. Other Considerations

Sources of errors for this research will be like those discussed in Chapter 2. Areas of agriculture and urban developments that were outside of the masked areas would present a potential source of error. As discussed in Chapter 2, efforts were made, using high resolution imagery, to remove these areas, so potential errors would be minimized. Thus, any area that should have been removed but was not would be a potential source of error. Additionally, it was reported in Chapter 2 that high densities of mustard skeletons are believed to cause overpredictions. Where abundant, mustard skeletons would be another potential source of error in the analysis.

A major assumption of this study, is that the land cover within the study area remained relatively unchanged of any major land altering events. There was no attempt to mask out any agriculture or urbans developments for any year other than 2015. Thus, changes that occurred through the period of the time series (1985-2016) that caused any of the above-mentioned sources or errors to become present within the study area could potentially cause prediction errors. Major changes within the study area are believed to be minimal because most of the area analyzed was grazed rangeland that is not expected to experience any significant land cover alterations.

6. CONCLUSION

Time series analysis is an important asset in a manager's toolbox that can lead to a better understanding of the dynamics of rangeland components. This research was effective in utilizing archived, publicly available, imagery to achieve landscape scale information of year-to-year changes of medusahead in an area of the Channeled Scablands of eastern Washington. This research provided an estimation of a remotely sensed time line of the medusahead invasion which shows support from documented and personal accounts of the area. The temporal dataset allowed the characterization of the study area into areas that may provide vital clues that could improve management approaches that mitigate medusahead invasion. To acquire similar information/results would have been expensive and would have taken years with traditional ground-based approaches. This research seems to present an option for land managers that need a quick, cost-effective method for gaining information that can lead to better preventing, controlling, and rehabilitating western rangelands invaded by medusahead.

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TABLES AND FIGURES

Table 4.1
The results from the questionnaire that was sent to individuals familiar with the study area from 1985-2016.

Responder	First Noticed Invasion	Became Dominant
Producer 1	Early 1990's	2002-2003
Producer 2	Early-Mid 1990's	Mid 2000's
Weed Specialist 1	1991-1995	2001-2005

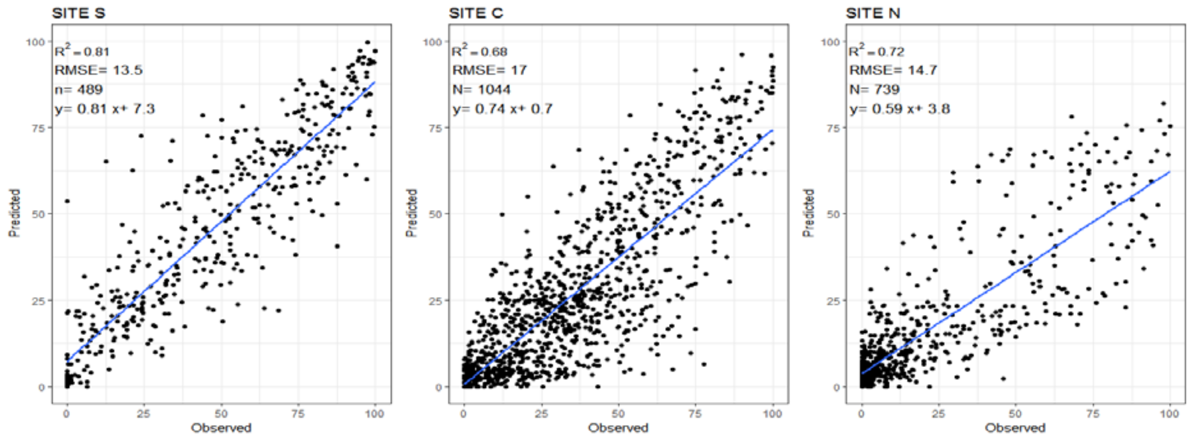

Fig. 4.1. Results of the independent tests used to measure the predictive performance of the temporal model near (Site S) and away (Sites N and C) from the training location.

Fig. 4.2. a) Time line of the annual mean fCover from 1985-2016. Red stars represent years that were interpolated due to missing data. **b)** Trend assessment from the Mann-Kendall test.

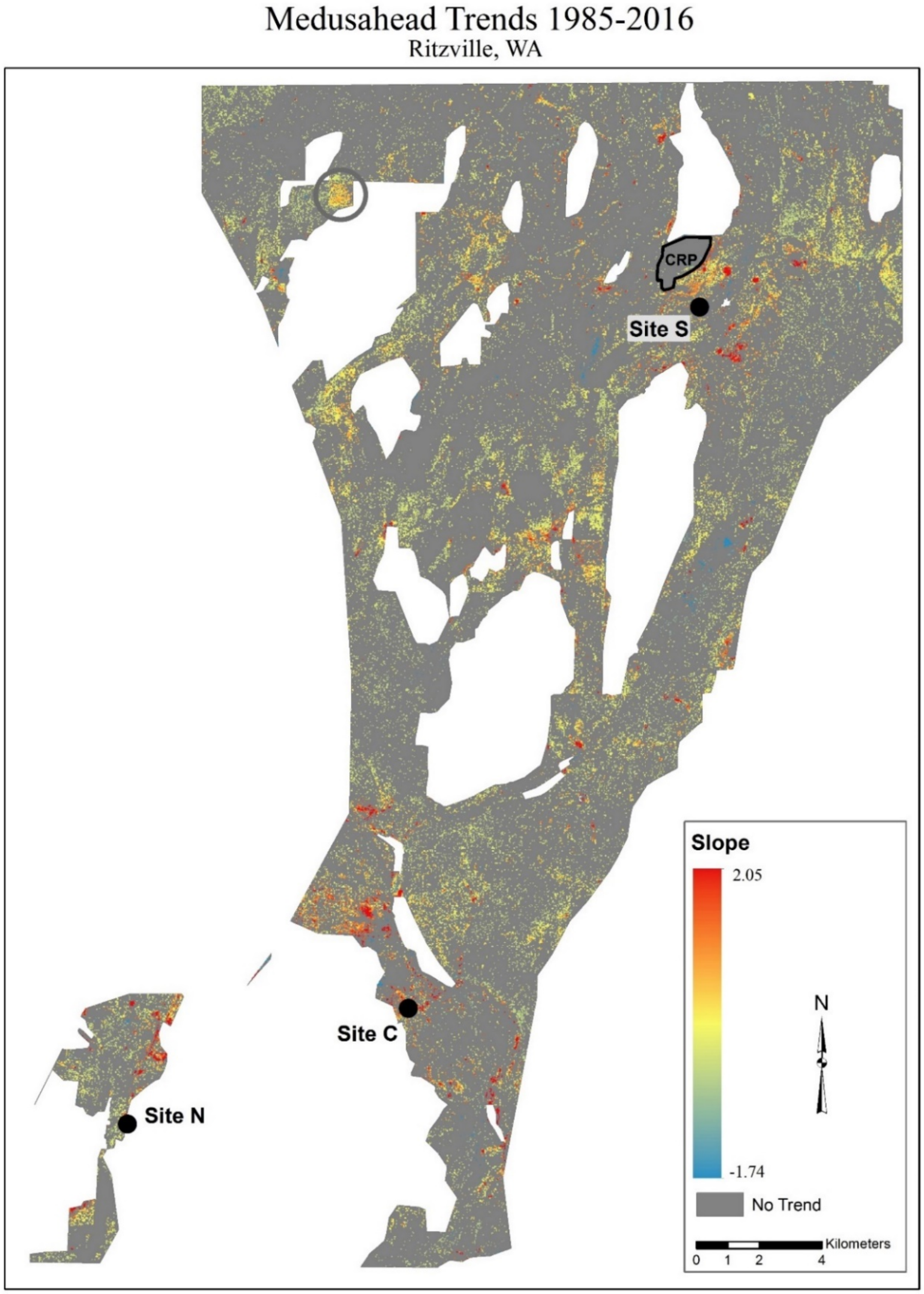

Fig. 4.3. Per-pixel medusahead trends and magnitude of change from 1985-2016.

CHAPTER 5

SPATIAL AND TEMPORAL ANALYSIS OF REMOTLEY SENSED RASTERS CONTAINING ESTIMATED MEDUSHEAD COVER IN THE CHANNELED SCABLANDS OF EASTERN WASHINGTON

ABSTRACT

Computer-based tools such as Geographic Information System (GIS) and remote sensing have aided invasive weed management by creating landscape scale distribution maps that benefit land managers. These maps can supplement management plans by directing management, identifying dispersal pathways, and providing a better understanding of the invasiveness of certain target weedy species. Medusahead is an aggressive, invasive annual that has been harming rangeland plant communities and increasing costs of ranching operations. This study explored spatial and temporal datasets containing estimates of medusahead cover in the Channeled Scablands region of eastern Washington. The objectives of this study were to understand some of the drivers for the temporal and spatial patterns of medusahead cover emerging from these datasets by identifying “high-risk” dispersal sites and climatic influences medusahead changes through time. The practicality of remote sensing on weed control was explored by creating a map that categorized the landscape into management strategies areas. This research identified watering points, corrals, and anthropogenic structures to be “high-risk” dispersal pathways that should receive high priority in controlling the additional spread of medusahead. Additionally, this study identified climate variables and periods of the year which could represent constraints for the expansion of the weed across the

landscape. Precipitation during January-March, June (t-0), as well as temperatures in May (t-2) represent key periods and events which affected medusahead cover on the temporal dataset of this research. This approach can aid land managers in making quick and informed decisions about grazing, mechanical and/or chemical applications for maximum efficiency in controlling invasive species like medusahead.

1. INTRODUCTION

Medusahead (*Taeniatherum caput-medusae* [L.] Nevski) is a non-native winter annual that has been proliferating through rangelands in the western United States since the late 1800's (Howell, 1903). Dispersal vectors such as vehicles, livestock, and wildlife have aided in the plant expanding its range by up to 12% annually (Rice, 2005; Davies et al., 2013). Recent estimates have suggested medusahead has invaded 950,000 ha (2.35 million ac) in 17 western states, including nearly 49,000 ha (121,000 ac) in eastern Washington (Duncan et al., 2004; Rice, 2005). The invasion is a serious economic and ecological concern, resulting in severe consequences that are often difficult to reverse (Young & Mangold, 2008; Kyser et al., 2014). Competitive characteristics have allowed medusahead to: drastically reduce forage capacity by nearly 90% (Davies & Svejcar, 2008), displace native plant communities, and alter the functionality of ecosystem by disrupting nutrient, water, and fire cycles (Young & Mangold, 2008; Kyser et al., 2014).

Germination of medusahead seedlings generally occurs in the fall but can also occur during the winter and spring months, which can lead to sequential flushes of new plant growth (Sharp et at., 1952; Young, 1992; Kyser et al., 2014). Following germination, growth will continue until medusahead reaches maturation in early summer, typically two to four weeks later than other annual grasses (Hironaka, 1961; Young, 1992). Medusahead can thrive under different precipitation and temperature regimes (Young et al., 1968; Dahl & Tisdale, 1975; Leffler et al., 2013) while other species remain dormant or have difficulties developing under the same conditions (Clausnitzer, et al., 1999; Leffler et al., 2011). This jump-start in development gives medusahead advantages to inhibit the growth of rival species through resource allocation (e.g., water, nitrogen etc.) (Hironaka, 1961; Nafus & Davies, 2014).

Medusahead phenology can differ greatly from different locations (Young et al., 1970). High phenotypic plasticity has been suggested as a key factor that contributes to the success of invasive species, like medusahead (Richards et al., 2006; Leffler et al., 2011). This allows adaptations to characteristics such as germination, growth/development, and seed production so the plant can remain competitive in a variety of different environments (Young et al., 1970; Leffler et al., 2011; Leffler et al., 2013). This suggests that management approaches found to be successful in the prevention and control of medusahead may not be universal but instead site-specific. Instead, Nafus & Davies (2014) suggest that to be successful, management practices may need to be tailored to specific sites, with considerations to environmental conditions and the management objectives. This type of detailed site-specific assessment may allow for the detection of sensitive characteristics that could be utilized for improved preventative and rehabilitation management (Leger, 2013; Uselman et al., 2014).

Davies et al. (2013) reported that the invasion of medusahead is not random and thus GIS and remote sensing technologies may help land managers discover and/or build upon management approaches. Remote sensing can help enhance invasive species management programs by improving the understandings of spatial and temporal dynamics (Bradley & Mustard, 2006; Bradley & Marvin, 2011; Boyte et al., 2015). This study seeks to derive information, from remotely sensed raster datasets, that would be valuable in improving the understanding and management of medusahead in an area of eastern Washington that has been challenged by the invasion of this weed. By analyzing fractional cover (fCover) estimates, the objective of this study was to explore the practicability of utilizing remotely sensed datasets by identifying high-risk dispersal sites, climatic influences and providing a product that can aid in directing management strategies. A hypothesis is that if remote sensing techniques can produce landscape estimates that are representative of medusahead cover and its changes through time, then influential information can be obtained about the spatial and temporal dynamics of medusahead in the area.

2. STUDY AREA

The study was conducted within the Channeled Scabland region of eastern Washington and consisted of 37,178 hectares (91,868 ac) of rangelands southeast of Ritzville, WA (46°48.23’N, 118° 16.98’W; 434 m). The vegetation community was once categorized as steppe and shrub-steppe with climax communities being dominated by *Artemisia tripartita*, *Agropyron spicatum* and *Festuca idahoensis* (Daubenmire, 1970; Franklin & Dyrness, 1973) but is now dominated by annual grasses, such as cheatgrass; medusahead; and weedy forbs fiddleneck (*Amsinckia intermedia* Fisch. & Mey), tansy mustard [*Descurainia pinnata* (Walt.) Britt.], rush skeletonweed (*Chondrilla juncea* L.), black mustard [*Brassica nigra* (L.) Koch in Roehl], and filaree [*Erodium cicutarium* (L.)

L'Hér.] (Ralphs et al., 2011). Areas with wheatgrass species ([*Pseudoroegneria spicata* (Pursh) A. Löve], [*Agropyron cristatum* (L.) Gaertn], [*Thinopryum ponticum* (Podp.) Z.-W. Liu & R.-C. Wang]) and basin wildrye [*Leymus cinereus* (Scribner & Merrill) A. Löve] were present but were scarce.

The climate is semiarid with a 50-year average annual precipitation of 272 mm (NOAA, 2017). The elevation slopes from the north to south and ranges from 600m to 323m. Large elevated areas, which are generally 45-75m above the surrounding rangelands, tend to increase in frequency moving further south. The tops of these areas have deep, high-quality soils and are typically used for agricultural production, while the surrounding areas are generally used for grazing livestock and are scattered with agriculture and urban developments.

Extensive grazing and repeated fires have led to many areas becoming dominated by annual species (Daubenmire, 1970; West & Young, 2000). Today, the competitive ability of medusahead has displaced many areas once dominated by cheatgrass which has led to medusahead becoming the dominant player in large portions of eastern Washington (Hironaka, 1994). Since the 2000s, herd sizes in the area have been reduced in some cases by 50% and producers have had to change practices to mitigate losses from the invasion of medusahead. These changes include: adding additional farming operations, altering historic grazing practices, modifying calving strategies, and increasing supplemental forage (Information gathered by interactions with producers from the region).

2.1. Site Descriptions

The model development process took place at three sites spanning over a 33 km transect. This was done to take advantage of any variations in rangeland conditions and environmental factors while providing independent test sites for the prediction model. Site S, located about 26 km southeast of Ritzville, WA (47°03.16'N, 118°02.79'W, 553 m), consisted of approximately 3,209 ha (7,930 ac) of grazed rangelands, with roughly 187 ha (462 ac) being used in the United States Department of Agriculture (USDA) Conservation Reserve Program **(**CRP). The CRP portion of the site was heavily dominated by tall perennial and wheatgrass species [*Agropyron cristatum* (L.) Gaertn], [*Thinopryum ponticum* (Podp.) Z.-W. Liu & R.-C. Wang]) [*Leymus cinereus* (Scribner & Merrill) A. Löve]. The soil taxonomy falls into the categories of Benge gravelly silt loam and Loamy to Coarse-loamy, mixed, superactive, mesic typic and lithic haploxerolls (Anders-Kuhl extremely rocky silt loams). Site C, located about 26 km south of Site S (46°50.29'N, 118°09.99'W, 469 m, consisted of approximately 60 ha (148 ac) of grazed rangeland. The soil classification is the same as Site S (Benge gravelly silt loam). Site N, located 33 km south southwest of Site S (46°48.23'N, 118° 16.98'W, 434 m), consisted of approximately 73 ha (181 ac). The soil taxonomic class is a coarse-loamy over sandy or sandy skeletal, mixed, superactive, mesic calcidic haploxeroll (Stratford silt loam).

3. MATERIALS AND METHODS

Validated fCover datasets, created from prediction models, were used to explore spatial and temporal dynamics of medusahead within the study area. Predictions for each dataset were restricted to areas outside of agricultural and urban developments and steep elevation changes. Spatial analysis consisted of identifying potential high-risk dispersal sites and characterizing the study area into management strategies which are based on invasion level. The temporal analysis consisted of identifying any potential climatic drivers of the annual mean estimates of the study site. The climate data was downloaded from the National Centers for Environmental Information (NCEI) National Oceanic and Atmospheric Administration (NOAA) website. The data was downloaded from two ground stations near the study area and averaged between the two (47°11.39'N, 118°37.72'W; 46°99.83'N, 118°57.10'W) before analysis took place.

3.1. Model Development and Prediction Datasets

For this study, spatial and temporal analysis was conducted on 30m raster datasets that were created in Chapters 2 and 3, respectively. The datasets represent fractional cover (fCover) values which were estimated using prediction models that were created using the same methods, dependent dataset (fCover), and predictor variables outlined in Chapter 2. Using R (R Development Core Team, 2016), the prediction performance was validated by linear regression of non-training pixels and their associated fCover estimates at all three sites. Identifying an appropriate accuracy threshold was done by assessing R^2 values from research predicting similar rangeland components in western states of the U.S. (Peterson, 2005; Sant et al., 2014; Xian et al., 2015). The threshold of a $R^2 > 0.75$ from the independent test at Site S was used to characterize an acceptable predicting performance. Once a model's performance was deemed acceptable, it was then applied to the predictor variables of each year to create the spatial (2015) and temporal (1985-2016) datasets.

3.2. Spatial Analysis

The spatial analysis portion of this research was done using the 2015 dataset created in Chapter 2. This study was interested in identifying potential high-risk dispersal sites and demonstrating the utility of the dataset by creating a strategy map that could aid in directing management actions. The map was based upon a management framework founded on invasion levels of medusahead and is described in Nafus & Davies (2014). It was expected that results from this spatial analysis could be used to show how a remotely sensed dataset may aid in creating more effective and cost-efficient management plans.

3.2.1 Dispersal Sites

This study was interested in exploring the hypothesis that medusahead fCover estimates would be higher around areas related with high activity of dispersal vectors. One-meter 2015 National Agriculture Imagery Program (NAIP) imagery was used to identify four features that would be associated with high human or animal activity. Locations of watering points, corrals, gravel pits, and anthropogenic structures were identified by methodically scanning the NAIP image. An anthropogenic structure included any human built object and any associated objects (i.e. barns, houses, driveways, farm equipment). When identified, a marker was placed in the center of that feature. Upon the occurrence of additional feature types within the anthropogenic structure feature's boundary (i.e. corrals, water points), the additional features were ignored, and one marker was placed in the center all associated objects. In addition to the four feature types, 200 markers were generated and randomly dispersed throughout the study area using ArcGIS software (ESRI, 2017). One hundred-meter buffers were created around each marker to form a defined extent to measure differences in mean fCover values. In situations where a 30m pixel fell both within and outside of the study area and buffer extents, the software made the decision whether to include or remove that specific pixel from analysis. Mean values were calculated from fCover values within each buffer using ArcGIS software. These values were used to characterize the differences in fCover estimates in relation to each feature type.

3.2.2. Management Strategy Map

The objective of this portion of the study was to show the practicability of the 2015 spatial dataset by creating a map that would aid in directing and creating more cost-efficient management plans in the area. A management framework, based on invasion level, was used to characterize the landscape into strategy areas. The framework included three management strategies (prevention, early detection, and rehabilitation) and suggested associated management actions. Each pixel of the study area was classified into three bins based on user defined thresholds. Each pixel was categorized into either prevention (0-5%), early detection (5-25%), or rehabilitation (25-100%) areas.

3.3. Temporal Analysis of Climatic Variables

The time series dataset, created in Chapter 3, was used to conduct the temporal analysis using the stats package of R (R Development Core Team, 2016). The dataset consisted of 32 mean fCover estimates for the study area corresponding to each year of the time series. Monthly precipitation (mm) and minimum, maximum, and average temperature (˚C) data were downloaded and used to create exploratory variables for each year of the time series (1985-2016). Each year consisted of 53 variable which were: (1)

averaged 12-month (July-June(mm)), (48) monthly (e.g. July (mm), July Maximum(˚C), July Minimum(˚C), July Average(˚C)), and (4) averaged quarterly periods (July-September (mm); October-December (mm); etc.). Medusahead plants complete their life cycles in the early summer months (Kyser et al., 2014; Nafus & Davies, 2014). Following maturation, climate conditions would have no effect on the current year's estimate of medusahead cover. These conditions would rather show potential influences on the following years populations. Because of this, this study defines a "medusahead year" beginning on July 1st and ending on June 30th. This means that climate conditions recorded in months July-December of 2014 and January-June of 2105 were analyzed as to have influence on the annual fCover estimate of the year 2015.

Cross-correlation (Venables & Ripley, 2002) was used to measure the strength of relationships between the annual fCover estimates and the climate variables at both time (t), and lag times (t-1 and t-2). Randomness and the strength of each relationship was evaluated by assessing cross-correlograms and the correlation coefficient (r = -1, perfect anticorrelation; r = 0, no correlation; r = 1, perfect correlation). Before analysis, the fCover variable (dependent) was log-transformed and both the fCover (dependent) and climate variables (independent) were linearly detrended to meet the assumptions of the test (constant variance, non-linearity). (Silvertown et al., 1994; Weimerskirch et al., 2003; Horvatic et al., 2011). Influential observations were evaluated using Cook's distance assessment (Cook, 1977).

3.4. Accuracy Assessments of Prediction Models

As described in Chapter 2, accuracy for both the spatial (Chapter 2) and time series (Chapter 3) datasets were assessed by regressing withheld (observed) non-training fCover pixels against their associated predicted fCover pixels using the R environment (R Development Core Team, 2016) The metrics used to evaluate prediction performances were Root Mean Squared Error (RMSE) and the correlation determination (R^2). The RMSE is a measurement of the variance between the predicted and observed values and is reported in the same unit as the modeled variable. The R^2 is a number representing a measurement of the amount of total variation that can be explained by the model. Both metrics have been used in ecological remote sensing research as a measurement of prediction performance (Homer et al., 2013; Xian et al., 2013 Boyte et al., 2015).

4. RESULTS

4.1. Accuracy Assessments of Prediction Models

Because this research used datasets created in prior chapters, the results from the accuracy assessment of the spatial (Chapter 2) and temporal (Chapter 3) datasets are identical to what was reported in Chapters 2 and 3, respectively, but are still listed below.

4.1.1. Spatial Dataset

From Chapter 2, there were 9,000 pixels, from Site S, utilized to train the prediction model. There were 475 pixels from Site S, 1,003 from Site C, and 739 from Site N used for accuracy assessment tests. This resulted in a RMSE 13.9 and a R^2 of

0.801 at Site S, a RMSE of 15.6 and a R^2 of 0.625 at Site C, and a RMSE of 14.3 and a R^2 of 0.727 at Site N. All tests resulted in a p-value < 0.01.

4.1.2. <u>Temporal Dataset</u>

From Chapter 3, there were 9,261 pixels, from Site S, utilized to train the prediction model. There were 489 pixels from Site S, 1,003 from Site C and 739 from Site N utilized for independent tests of the for the dataset This resulted in a RMSE 13.5 and a R^2 of 0.81 at Site, a RMSE 17.0 and a R^2 of 0.68 at Site C, and a RMSE 14.7 and a R^2 of 0.72 at Site N. All tests resulted in a p-value < 0.01.

4.2. Spatial Analysis

4.2.1. <u>Dispersal Sites</u>

In addition to the 200 randomly distributed markers, there were 122 locations, identified on the 2015 NAIP image, categorized into one of the four feature types (watering points, corrals, gravel pits, anthropogenic structure). The 122 locations consisted of: 7 corrals, 70 water points, 33 anthropogenic structures, and 12 gravel pits. The 100m buffer around each of the 122 locations was used to calculate the mean of estimated fCover values. The results are characterized using a boxplot shown in Fig. 5.1. The corral feature type resulted in the highest median value of mean fCover at 47.5 %. This was followed in succession by water points and anthropogenic structures of 37.5% and 32.4% median values, respectively. The gravel pit feature type showed the lowest median value of fCover at 12.9% while random points showed the second lowest median value of 14.3%.

4.2.2. Identification of Management Strategy Areas

The results from the management area classification resulted in a map that categorized the 2015 fCover dataset into areas that may benefit from preventive (< 5%), early detection (5-25%), and rehabilitation (> 25%) management strategies (Fig. 5.2). This resulted in 4,554 ha (11,254 ac) classified as preventive, 21,768 ha (53,790 ac) as early detection, and 10,855 ha (26,824 ac) as rehabilitation areas.

4.3. Temporal Analysis of Climatic Variables

Relationships between annual fCover estimates and 53 climate variables at t-0, t-1, and t-2 were analyzed in this study. From evaluating the cross-correlograms, six variables showed non-randomness and resulted in significant correlations, at the 5% level (Fig. 5.3). At t-0, precipitation (mm) in March (r = 0.39), June, (r = 0.38), and the quarterly period of January-March (r = 0.45) showed to have a moderate positive influence on the temporal dynamics of the dataset. At t-2, maximum (r = 0.38), average (r = 0.42), and minimum (r = 0.41) temperatures (˚C) in the month of May also showed moderate positive influences on the dataset (Fig. 5.4). A locally weighted smoother line (lowess) was fitted to the six graphs to help show direction of relationships. From Cook's distance analysis of influential points, only one relationship that showed a change > ± 0.05 of the correlation coefficients was identified. Upon removal of the influential observation from this relationship, the correlation coefficient of precipitation (mm) in June, at t-0, increased from, r = 0.38 to r = 0.44. Real-world data, that is associated with climate conditions, can sometimes be unpredictable and produce outlier records. However, the influence on the correlations was minimal (all but one < ± 0.05 change on *r*) and thus removal of outlier observations was not necessary. Thus, no data was removed to create the results depicted in Fig. 5.4.

5. DISCUSSION

5.1. Spatial Analysis

Alone, medusahead disperses to relatively short distances, thus relying on vectors such as humans or livestock to get distributed across larger spatial scales (Monaco et al., 2005; Davies, 2008). Davies et al. (2013) reported greater readings of medusahead near areas of unimproved roads and near livestock trails; these were compared to randomly placed transects. The results from the dispersal site analysis displayed similar findings, as the median value for the random features was lower than all but one (gravel pits) of the feature categories. The outliers, in Fig. 5.1, suggest that random points can still be found near areas of heavier fCover estimates but are generally uncommon above 40%. The results from this analysis seem to support findings of Davies et al., (2013) from the standpoint that distributions of the medusahead invasion are not random.

From a species that is highly dependent on dispersal vectors, caution should be given to areas associated with high densities of potential vectors. Greater amounts of medusahead in these areas can lead to increased dispersal across a landscape. These areas should be deemed as “high priority” when considering management plans designed to eradicate and prevent reinvasion, so medusahead dispersal can be reduced. Information from this analysis should be used to educate land managers, livestock producers, and recreationalists about the dangers of transporting medusahead and help direct monitoring and management efforts towards higher-risk areas.

Continuous datasets can provide a more realistic and robust representation of a landscape. These datasets can provide more telling information about detecting gradual shifts in population dynamics compared to discrete datasets (Fernandes et al., 2004; Wegmann et al., 2016). The 2015 fCover dataset allowed for the determination of thresholds to best meet the management framework discussed in Nafus & Davies (2014)**.** A 5% threshold, for the upper bound of the preventive category, was defined to account for the potential of over-predictions or Type I errors (discussed in Chapter 2 and Chapter 3). This also produced a more visual and discrete representation of the three management strategies. The 25% threshold was chosen because it represented a fair threshold in which areas < 25% medusahead cover would still be responsive to site eradications treatments rather than complete rehabilitation treatments. Fig. 5.2 is an output produced from classifying each 30m pixel of the 2015 fCover dataset into one of the three management strategies based on fractional thresholds (Prevention 0-5%, Early Detection 5-25%, Rehabilitation 25-100%). This type of output can be put in the hands of land managers for prioritizing and directing management efforts towards sites where they would be most effective. An example of this would be the large prevention area in the center of Fig. 5.2; land managers could consolidate and focus efforts to prevent medusahead invasion in this area. Such actions may entail the creation of “strong hold” areas in which improvements could be expanded from those locations.

Remote sensing technologies should not be look at as a way to replace traditional ground-based methods. Instead, these technologies need to be viewed as an additional tool in the manager’s toolbox to complement or supplement other management methods. Fig. 5.2 depicts how remote sensing technologies can work with current research to formulate management plans that can be more effective and thus more cost-efficient to land managers.

As discussed in Chapter 2, the methods in this study may not detect lightly dispersed areas of medusahead. Because of this, it should not be assumed that medusahead is not present in areas characterized by preventative management. Thus, it may prove beneficial for managers to use the Management Strategy map, in Fig. 5.2, in a relative versus an absolute sense. The map could provide more value in directing ground assessments crews to investigate why certain areas are showing relatively higher cover estimates than others. Ground assessments may also help calibrate the classification thresholds and improve the overall map.

5.2. Temporal Analysis

Temperatures in the month of May, at t-2 had a moderate influence on the annual mean estimates of medusahead fCover (Fig. 5.4). This is characterized by warmer temperatures being generally associated with years of greater medusahead cover. Leffler et al. (2013) reported that adult medusahead plants showed a considerable increase in the absorption rate of nitrogen at 25 ˚C, compared to colder temperatures (5 ˚C, 10 ˚C, 15 ˚C). Additionally, this increase represented a large advantage in relation to perennial species (i.e. bluebunch wheatgrass ([*Pseudoroegneria spicata* (Pursh) A. Löve], crested wheatgrass [*Agropyron cristatum* (L.) Gaertn]) and cheatgrass, grown under the same conditions. In contrast, colder temperatures have been reported to benefit germination rates, root development, and growth of medusahead, especially during the early stages of development (Harris & Wilson, 1970; Clausnitzer et al., 1999; Leffler et al., 2011).

Medusahead's ability to optimize its performance across different temperatures regimes may aid in its invasibility and provide advantages as habitats become altered by climate change. This temporal analysis suggests how temperatures might influence medusahead populations in future years and help explain the findings of this research. As colder temperatures during the winter and spring months suppress perennial species, medusahead may be able to develop with lower competition for essential resources. This likely benefits medusahead later in its life cycle, when a relatively large root system could allocate more resources, such as nitrogen. An increase in nitrogen allocation as temperatures increase before maturation may produce a last-minute pulse of vigor. If this pulse enhances seed production on a current year, it could act as a catalyst for future generations by creating a cascading effect of additional individuals. The influx of new seedlings may produce additional individuals and thus additional seedlings leading to higher populations of medusahead in subsequent years, as observed in the temporal analysis.

Precipitation for the quarterly period of January-March, the month of March, and the month of June of a current year (t-0) showed to have an influence on the annual mean estimates of medusahead fCover (Fig. 5.4). This is characterized by increasing precipitation during these periods being generally associated with years of greater medusahead fCover. This may be explained by a more competitive root system that allows medusahead to better allocate resources when they become available. When grown under similar conditions, medusahead has shown advantageous root development over cheatgrass and perennial seedlings (bluebunch wheatgrass; crested wheatgrass) during the months of December to June (Hironaka, 1961). Increased precipitation in the early months of the year (January-March, March) would provide a resource that would be available to medusahead with minimal competition. This resource may relate to increases in additional germinations and fitness of individuals for that year. The higher precipitation in June found to be benefiting medusahead was unexpected as medusahead typically is close to reaching maturation during this period. This situation may be explained by medusahead maturing typically two-three weeks after cheatgrass and thus requiring moisture for a longer period of time (Dahl & Tisdale, 1975). A hypothesis for why medusahead years increase with precipitation in June would be that an influx of additional resources that may produce increases in last minute growth and maturation before senescence of the plant. This may produce an increase in biomass within the population that helps fill space and thus produces higher medusahead estimates.

Scientists have been interested in identifying more desirable species that can better resist invasion and reinvasion of medusahead that will aid in prevention and revegetation efforts (Sheley et al., 2008; Davies, 2010; Stonecipher et al., 2016). The results from the temporal analysis identified potential critical periods when temperature and precipitation events seem to influence on the population dynamics of medusahead in the area. This information could potentially lead to the creation or improvement of management approaches aimed at identifying better competitive species to be used in prevention and revegetation of medusahead invaded sites. This may lead to the development of more competitive seed mixes that could be used in the area. This could help reduce costs by increasing the effectiveness and efficiency of management plans which can then lead to additional lands being treated.

5.3. Other Considerations

Further analysis of the precipitation records for the last 50 years revealed a recent increase in the amount of drought years (Fig. 5.5**)**. There were 22 years, out of the 32 years used in the time series dataset (1985-2016), that were at or below the 50-year precipitation average (1967-2016). Research has shown that invasive annual grasses are more competitive than perennial species, even when resources are limited (Monaco et al., 2003; James, 2008; Nafus & Davies, 2014). Although severe drought may reduce the competitiveness of medusahead, dormant seedbanks can quickly replenish landscapes during a single wet year, allowing for continued dominance of the landscape (Young et al. 1998; Kyser et al., 2014). Fig. 5.5 shows that since the early 2000s non-drought years (above the 50-year average) are occurring in a larger and less frequent pattern compared to prior years. This pattern has been reported to benefit the spread of medusahead over other invasive annuals (cheatgrass; ventenata (*Ventenata dubia* (Leers) Cos.)) and may be enhancing the spread of the species ensuring future dominance in the presence of climate change (Bansal et al., 2014).

6. CONCLUSION

This research has provided examples of valuable information that can be delineated from remotely sensed datasets. This analysis provided a relatively quick and cost-effective approach to gain information on the dynamics of medusahead that would be difficult and expensive to ascertain using other methods. The results of this analysis should prove useful to land managers and producers challenged with medusahead in the region. Due to the phenotypic variations of medusahead, these findings may be site specific and tailored research may be required. Remotely sensed data can provide landscape scale information that may not be available by other means. Landscape scale assessments may provide keys to unlock innovative ideas and applications that will aid developing and improving the management of rangelands threatened by medusahead.

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FIGURES

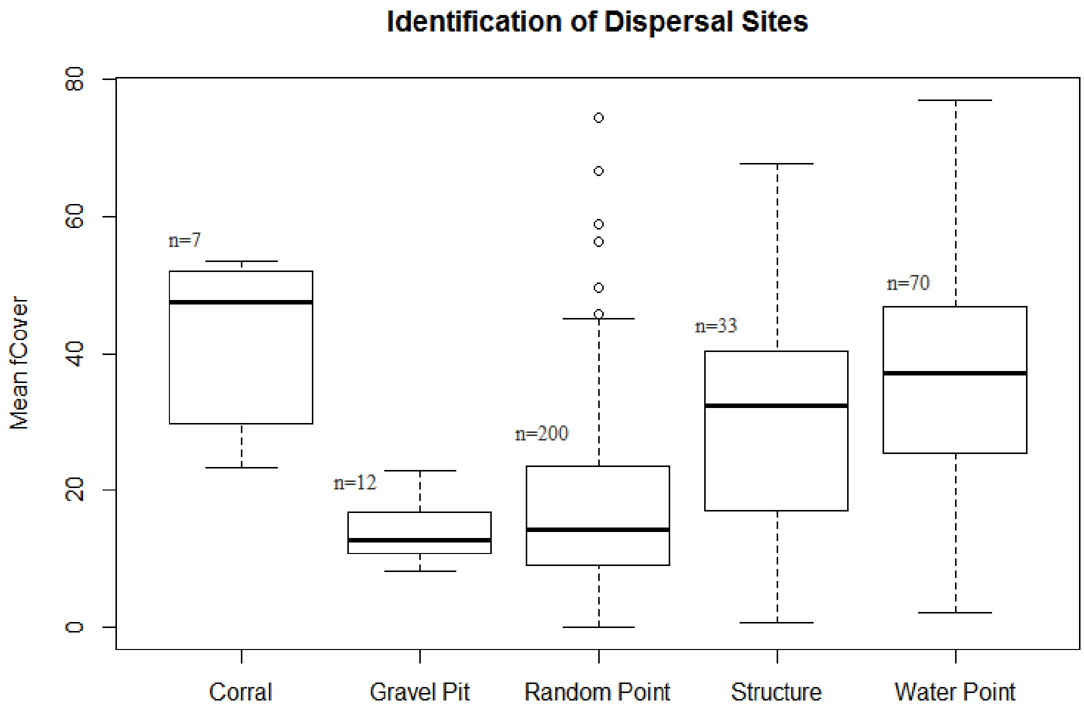

Fig. 5.6. Results of the dispersal site analysis that is showing the differences in mean fCover estimates associated with different features.

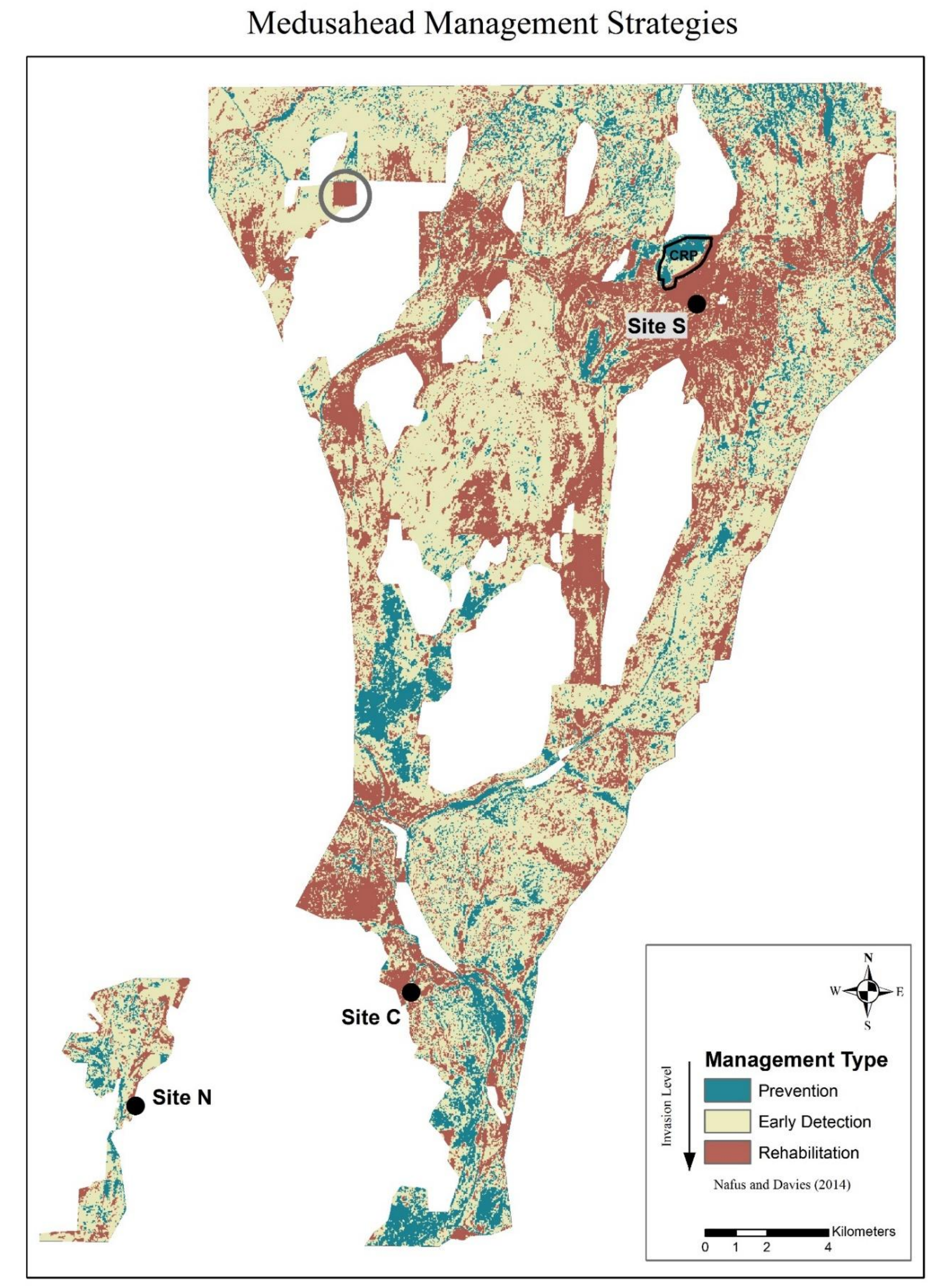

Fig. 5.7. Management Strategies map. Derived by classifying the 2015 continuous fCover dataset using thresholds based on invasion level.

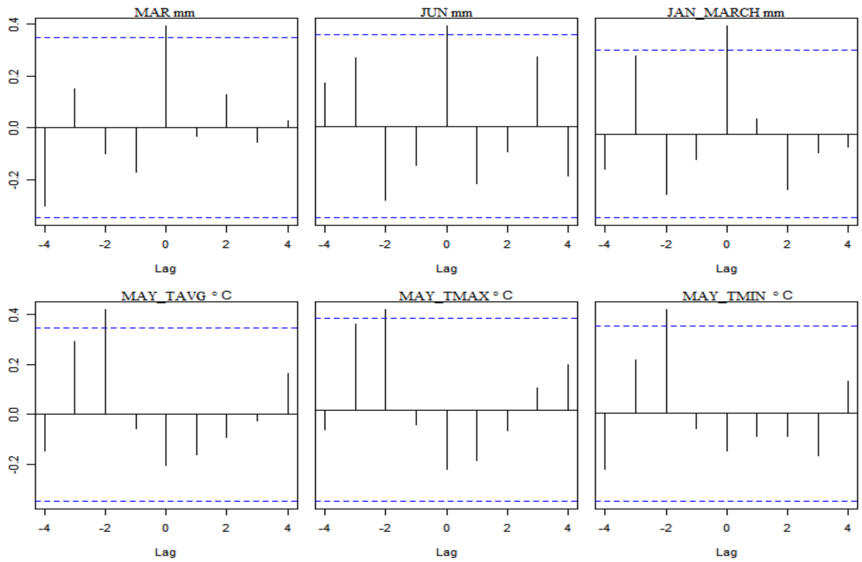

Fig. 5.8. Cross-correlograms of the six variables that showed non-randomness and resulted in significant correlations, at the 5% level.

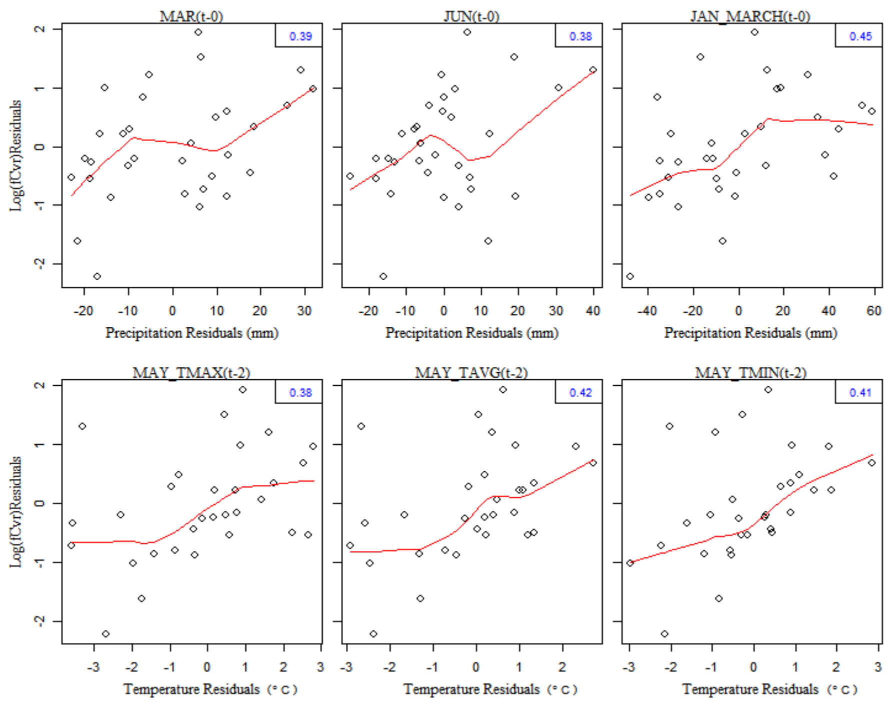

Fig. 5.9. Graphs showing the strength of correlation and relationship of the six significant climate variables. Each graph is fitted with a lowess line to help show relationships.

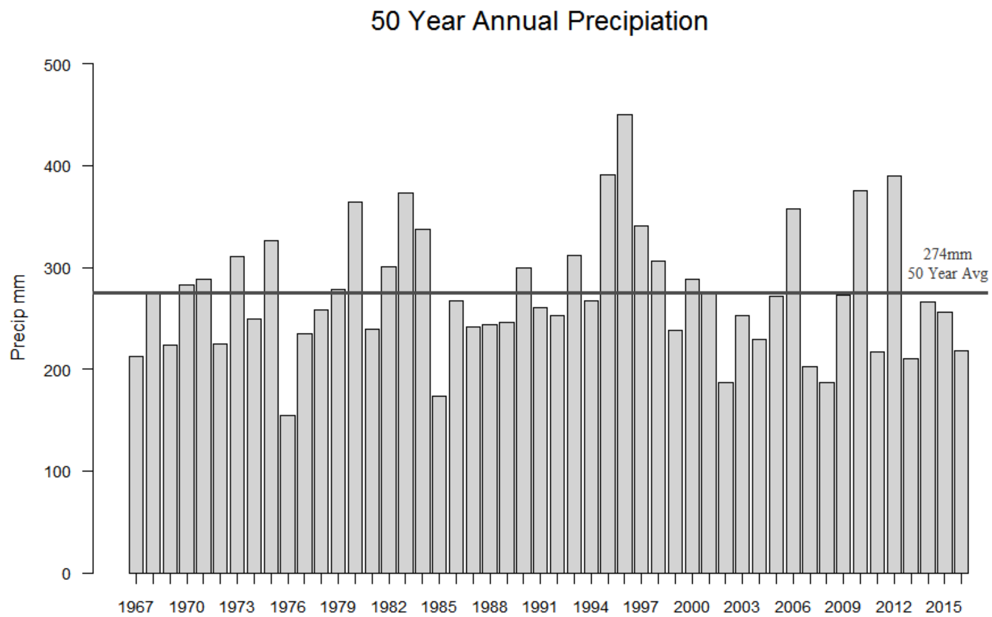

Fig. 5.10. Graph show the 50-year average annual precipitation from two NOAA ground stations near the study area.

CHAPTER 6

SUMMARY AND CONCLUSIONS

There is an unmet need to create ecological models which can help identify spatial and temporal characteristics leading to the improvement and development of influential management efforts that are aimed at the prevention and control of invasive species (Davies & Sheley, 2007). Remote sensing applications can help fulfill these needs by providing broad scale assessments of entire landscape systems. Although aerial assessments may lack an ability to ascertain fine scale measurements, ground-based research misses important and influential variables that occur outside of a sample plot. Remote sensing allows land managers to quantify and provide landscape-scale assessments to make more informed decisions on how to manage rangelands challenged by different factors such as weed invasion. Integration of remote sensing can help meet this objective by supplementing and developing sustainable successful programs that can aid with the continuation of improving and protecting western rangelands.

Western rangelands continue to be threatened by the vast expansion of medusahead. In the presence of a changing climate, the future of these threats may be exacerbated (Bansal et al., 2014). Medusahead has occurred in eastern Washington since the early 1900s but there has been a rise in the abundance and severity of the invasiveness of the plant in the region during more recent decades. Fifty-year ground-based station data shows signs of change regarding the precipitation regime in the region for the last 30 years, as above-average precipitation years have been occurring less frequently in recent decades. In the past, plant communities may have had access to the resources needed to repel large expansions of medusahead. As precipitation levels declined during drought years, this may have weakened perennial rangeland communities and acted as a catalyst to trigger the large expansions of annual grasses observed in the last three decades.

The continued persistence of the invasion is presenting growing challenges to producers in the Channeled Scabland region. Effective control and prevention techniques need to be identified so managers can improve eradication and rehabilitation efforts that are being used in the region. Individuals should be concerned with the serious implications and consequences that are associated with medusahead invasion.

Results from this research have shown that it is possible through specific spectral characteristics to delineate senesced medusahead monocultures from other rangeland components and accurately predict medusahead distribution in the landscape (Chapter 2). This research also shows that through a time-series analysis is it possible to use archived imagery to gain landscape-scale information about year-to-year changes of medusahead cover in rangelands (Chapter 3). Such analysis showed a cyclic nature of “high” and “low” years of medusahead cover. Results have identified potentially sensitive periods that may alleviate “high” medusahead years and that can be targeted to develop competitive seed mixes in prevention and rehabilitation efforts. This research also identified “high risk” dispersal sites that should be a priority in medusahead management to limit the expansion of the weed into new or rehabilitated areas (Chapter 4). Management priorities should remain determined to remove medusahead and replace this annual weed with more desirable species. Management programs need to be sustainable, effective, and constant. The public and government officials need to be educated on the dangers of medusahead invasion and what needs to be done to stop its expansion. Support should be given to the land managers trying to improve rangelands under the challenge of weed invasion. Archived imagery can help on this regard, as it would provide a quicker and cheaper means to understand the pattern of medusahead invasion and to build scenarios for potential expansions of the weed across the landscape into the future.

In summary, this research has applied remote sensing techniques to generate temporal and spatial predictions of medusahead in the Channeled Scablands region of eastern Washington. These predictions are supported by collected ground data (spatial) and qualitative reports (temporal). Results from this research show the potential for the use of remote sensing techniques to achieve key spatial and temporal information about medusahead cover quicker and more affordably compared to ground-based methods. This type of information is valuable and needs to be in the hands of land managers, so they can make influential and informed decisions on invasive species management. Integrating remote sensing into management plans can aid in directing and advancing management strategies so rangelands in the West can be improved and the invasion of medusahead can be prevented, controlled, and eradicated. Individuals need to be educated on the risks and consequences of the continued expanse of this plant so additional support can be given to those that can make positive impacts on improving and protecting western rangelands threatened by medusahead.

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