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Multi-temporal Remote Sensing of Rangeland Vegetation for Investigation of Fire-related Ecology at Canadian Forces Base Suffield, Alberta

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Multi-temporal Remote Sensing of Rangeland Vegetation for Investigation of
Fire-related Ecology at Canadian Forces Base Suffield, Alberta

by

Brent Smith

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ABSTRACT

Canadian Forces Base (CFB) Suffield, located in southeastern Alberta, faces pressure from a variety of competing land uses and requires geospatial tools to quantify and manage the effect of human activities (particularly military training-related fire) on ecosystem functions. I used multi-temporal remote-sensing techniques to model plant functional types (PFT; C3 vs. C4 grasses), as an indicator of ecosystem state. The best-performing model (overall accuracy = 74%, weighted kappa = 0.53) was compared against a spatial fire-history database digitized from the Landsat archive (1972 to 2007). Probit regression results revealed statistically significant relationships between PFT-derived ecosystem states and fire history ($P < .001$), but succession processes were different between ecological units. In general, this ecosystem is sensitive to repeated fire, with recovery taking decades. This research provides novel contributions to ecological knowledge in northern mixedgrass prairie, and outlines specific management actions required to maintain ecologically sustainable fire frequency.

PREFACE

This is a paper-based MSc. thesis. Chapters 2 and 3 have been submitted for publication in peer-reviewed journals, and have been approved by the Department of National Defence. Where Chapter 2 aims to create an accurate PFT map, Chapter 3 involves the development of statistical relationships between the PFT map and fire history at CFB Suffield. I am intellectually responsible for all of the works. I was the primary person identifying the research questions, designing the field-based research, undertaking the analysis and interpretation, creating the graphical and tabular results, and writing the manuscripts.

The full citation for Chapter 2 is: Smith, B., and G.J. McDermid. In review. Plant functional type classification using MODIS, temporal filtering, and ecological variables within the dry mixedgrass subregion of Alberta. *Canadian Journal of Remote Sensing*.

The full citation for Chapter 3 is: Smith, B., and G.J. McDermid. In review. Examination of fire-related succession within the dry mixedgrass subregion of Alberta using MODIS and Landsat. *Journal of Range Ecology and Management*.

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CHAPTER 1: INTRODUCTION

Canadian Forces Base (CFB) Suffield, one of three Canadian Army bases in Alberta, is comprised primarily of native mixedgrass prairie, providing habitat for 23 federally-listed species at risk including the burrowing owl (*Athene cunicularia*) and ferruginous hawk (*Buteo regalis*; COSEWIC 2011). With a total size of 2690 km², the base also provides land use opportunities for military training, military defence research, oil and gas development, and cattle grazing: land use activities that influence range health. In attempting to balance these competing values, CFB Suffield is bound by federal legislation and policy guidelines regarding the conservation of species at risk (*Species at Risk Act* 2003) and land use sustainability (Department of National Defence Sustainable Development Strategy 2006). For example, military training areas must develop sustainability indicators that demonstrate that management objectives are being achieved. In order to achieve compliance with federal regulatory objectives, research is required to identify and quantify the ecological status of the base, particularly within the military training area.

Central to the objectives of species-at-risk conservation and land use sustainability is the requirement to accurately quantify and detect changes in ecosystem status over time. The variety of land uses at CFB Suffield, particularly military training, can act as stressors to ecosystem functions (Althoff 2005; Anderson et al. 2005; Caldwell et al. 2006), but the disturbance associated with military training may also support the presence of species at risk, by maintaining appropriate habitat (Krausman et al. 2005; Warren et al. 2007). For example, the endangered Sonoran pronghorn antelope (*Antilocapra americana sonoriensis*) exhibits a preference for military target areas, likely as a result of the increased productivity of forage (Krausman et al.

2005). As a result, geospatial information which provides information on how habitats change in relation to disturbance is critical in understanding the ecological effects of military training, which includes changes to soil quality and changes to vegetation species composition by damage from traffic (Althoff 2005).

In addition to military traffic, fire is also a common disturbance on military training areas because of the use of incendiary munitions. The effects of repeated fire at CFB Shilo, Manitoba (also comprised primarily of native mixedgrass prairie), were shown to result in physical changes to the soil, the reduction of biomass production, shifts in species composition, and a reduction of moss and lichen cover (Shay et al. 2001). Fire remains a common disturbance at CFB Suffield, and both natural (lightning) and human-caused fires have occurred regularly since military training began in 1972.

Fire is a disturbance process which was historically present across the northern Great Plains, and is important for the maintenance of habitat conditions, by modifying vegetation structure and inducing vegetation-community succession (Daubenmire 1968). However, reliable information on sustainable and historical fire-return intervals in the area is difficult to compile. Where Wright and Bailey (1980) estimated historical frequencies of the northern Great Plains to be between 5 and 10 years, analysis of charcoal concentrations in lake sediments in Brush Lake near Sheridan, Montana, suggest that historical frequency ranged from 20 to 40 years, with fires declining as a result of European settlement (Umbanhowar 1996).

To highlight the importance of fire disturbance and its potential effects on species at risk, one only needs to look at the recent (2011) efforts to designate critical habitat for the Sprague's pipit (*Anthus spragueii*), a threatened species that is relatively ubiquitous within parts of CFB Suffield (Brenda Dale, Canadian Wildlife Service, *pers comm*). Critical habitat for pipit is

described as consisting of open areas of upland native prairie ≥ 65 ha in size, with native prairie management units in *fair* to *excellent* range condition (health) (Environment Canada 2011).

Destruction of critical habitat for Sprague's pipit includes (but is not limited to) loss of native vegetation or disturbance of soil substrate, and degradation of native prairie to poor range condition (health) (Environment Canada 2011). With documented changes to ecosystem functions as a result of repeated fire (Shay et al. 2001), fire has significant potential to affect the habitat of species at risk like Sprague's pipit.

The cumulative effects of historical and multiple concurrent land uses, including grazing and fire, on military training areas remain poorly understood (Anderson et al. 2005). In fact, in their review of existing literature of the ecological effects of military training, Anderson et al. (2005) identify a number of knowledge gaps, including: the development of indicators which respond to change and correlate with recovery; the identification of thresholds of catastrophic change where ecological change is irreversible; the derivation of meaningful ecological impact data at both fine and coarse spatial scales; the interaction between current and historical disturbances; and the interaction between military training and other land uses. Thus, geospatial tools are required which will enable managers to spatially quantify range health as an indicator of habitat quality and quantity. Once developed, such tools may permit the understanding of the relationship between range health and land use, in order to understand and define ecological thresholds, and most importantly, to define management objectives in ecologically meaningful terms.

The following sections provide further background in range ecology and ground-based rangeland monitoring, rangeland fire ecology, remotely sensing for rangeland management, and land use history of CFB Suffield.

1.1 RANGE ECOLOGY AND RANGE HEALTH

Ecosystems are difficult to describe in terms of time or space, but definitions are nonetheless important to provide context and to assist in the identification of management goals (Stringham et al. 2003). Rangelands are land on which the natural indigenous vegetation is predominantly herbaceous (grass or grass-like) and/or forbs and/or shrubs, and include grasslands, grazable forests, shrublands, and pastures, all of which are either grazed or have the potential to be grazed (Bedel 1998).

For rangelands, the fundamental land unit is the *ecological (range) site*, defined as “a distinctive kind of land with specific characteristics that differs from other kinds of land in its ability to produce a distinctive kind and amount of vegetation” (US Department of Agriculture Natural Resources Conservation Service 2003). Ecological sites are differentiated by factors including soils, aspect, and topography. Rangeland ecosystem states are complexes of vegetation structure and soil, which interact to produce a sustained equilibrium, expressed as a suite of vegetation communities (Stringham et al. 2003). The interaction between the structural attributes of soil and the vegetative communities, through the processes of energy capture, hydrology, and nutrient cycling defines resilience (a measure of how far the ecosystem can be displaced from equilibrium without irreversible changes) and resistance (a measure of an ecosystem’s ability to resist change; Stringham et al. 2003).

Vegetation succession is defined as the progressive replacement of plant communities leading to a potential natural/reference plant community (attaining equilibrium); primary succession describes the physical processes of vegetation and soil development during the initial establishment of vegetation, while secondary succession describes the process of community

changes following disturbances where vegetation is already established (Bedel 1998).

Vegetation succession is bidirectional: progressive succession describes the development of a succession series *towards* the natural/reference state; retrogressive succession (retrogression) describes the succession series *away* from the reference state, induced by disturbance processes (Glenn-Lewis and van der Maarel 1992). Seral states (ephemeral communities which are replaced as succession proceeds) typically progress in a predictable manner until the climax or reference state is reached, although alternative steady-states arising from irreversible transitions (thresholds) are also possible (Stringham et al. 2003). Succession can be visualized as a *state and transition model*, which generally describe communities (boxes) and pathways (arrows) in relation to disturbance and recovery from disturbance, with two-way arrows representing reversible changes, and one-way arrows representing irreversible thresholds (Fig 1.1). For example, the invasion of crested wheatgrass into northern mixedgrass native prairie is largely irreversible (Henderson and Naeth 2005), and represents an ecological threshold.

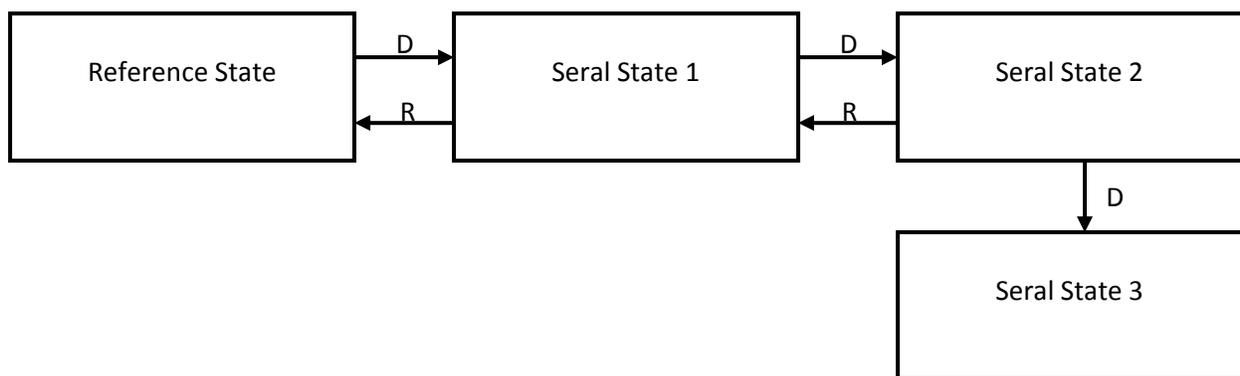


Figure 1.1: Theoretical state and transition model representing retrogression from reference state to seral state 3; D = disturbance-induced retrogression, R = recovery-induced progressive succession.

Ecological thresholds are used to describe non-linear and persistent reorganization of ecosystem states in response to gradual or discrete change in environmental patterns and drivers (Bestelmeyer 2006). Ecological thresholds are crossed when the primary ecological processes responsible for maintaining equilibrium degrade beyond the point of self-repair, requiring external energy inputs before the return to a previous state is possible (Stringham et al. 2003). Rangeland scientists and managers define rangeland indicators and thresholds in terms of vegetation and soil parameters (Pickup 1989; Milton et al. 1994) including:

1. changes in plant species, life-form, or physiognomic composition (Archer 1989);
2. changes in plant cover, density, productivity, or other attributes (Reeves et al. 2001, Washington-Allen et al. 2004);
3. changes in soil quality (Perkins and Thomas 1993); and
4. accelerated soil erosion (Pickup 1989).

However, while observed differences in rangeland indicators may be attributed to land use, they may also arise due to differences in ecological sites or natural variability (West 2003a). Thus, it is important to relate observed indicators to a comparable state, controlling for natural variability, in order to determine the status of ecosystems.

Ecosystem status can be evaluated in the context of range health, defined by the Province of Alberta as “the ability of rangeland to perform certain ecological functions” (Adams et al. 2005). These functions include net primary production, maintenance of soil/site stability, capture and beneficial release of water, nutrient and energy cycling, and *plant species functional diversity, which is an important consideration in the maintenance of habitat for a broad*

spectrum of wildlife species. Range health is measured by comparing the functioning of ecological processes on an area of rangeland to a reference standard, known as an *ecological site description*. Such standards are derived by long-term monitoring of vegetation characteristics and grazing (Adams et al. 2005).

Among the five criteria used to assess range health in Alberta, plant species functional diversity comprises 40 % of the total score; other factors include structural composition, litter biomass (defined as freshly fallen or slightly decomposed vegetal material; Bedel 1998), human-caused erosion, and the presence of weedy species. Functional diversity measures the actual species composition relative to an expected reference state. Within the dry mixedgrass subregion of Alberta, native cool season C3 species dominate healthy rangelands (Coupland 1950), and the increased cover of warm season C4 species is associated with decreased range health (Adams et al. 2005), as the productivity of C4 species is significantly lower than that of C3 species in this ecoregion (Barnes et al. 1983).

Rangeland health assessment methods are primarily based on the collection of point samples of vegetation and soil attributes at local spatial and limited temporal scales, which are then inferred to larger spatial scales and compared to reference sites (Washington-Allen et al. 2006). While ground-based monitoring has led to some understanding of ecosystem changes in rangelands, very few field-based surveys have been conducted with sufficient sampling intensity to account for the range of natural variability, or detect succession (Washington-Allen et al. 2003). This notion is reinforced by the general observation that the condition and trend of rangelands in the United States at subregional and regional scales is unknown (National Research Council 1994; West 2003a, 2003b). It can be argued that this is also true of Canadian rangelands, where management falls under a mix of federal and provincial jurisdiction, and

where land use is not necessarily managed by the same authority. Finally, the effects of fire on grazed rangeland (e.g., reduced productivity) require additional management considerations to facilitate grazing in the long-term (Erichsen-Arychuk et al. 2002).

1.2 RANGELAND FIRE ECOLOGY

Fire was once common across the northern Great Plains, playing a critical role in cycling nutrients, modifying plant structure, and inducing succession (Daubenmire 1968). However, the spatial extent and timing of fire in rangelands are significantly different than historical trends (Leach and Givnish 1996). Temporal trends of fire are typically described and measured as fire frequency (defined as the number of fires per unit time in a defined area), or fire-return interval (defined as the number of years between 2 successive fires in a defined area; McPherson et al. 1990).

The documented effects of fire are different between rangeland ecosystems in North America. In tallgrass prairie (Fig 1.2), where the dominant species are C4 grasses, fire has been shown to increase productivity (Wright and Bailey 1982). In contrast, fire in northern mixedgrass prairie (dominated by C3 grasses), fire reduces productivity (Clarke et al. 1943), and the recovery of litter biomass takes many years (Dix 1960). Similarly, fire in shortgrass prairie results in decreases in productivity, although the magnitude of effects is neutral to negative (Scheintaub et al. 2009). Moisture is a limiting factor for plant growth in semi-arid rangelands like the northern mixedgrass and shortgrass prairie (Scheintaub et al. 2009; Vermiere et al. 2011), and litter is a critical structural component which conserves moisture.

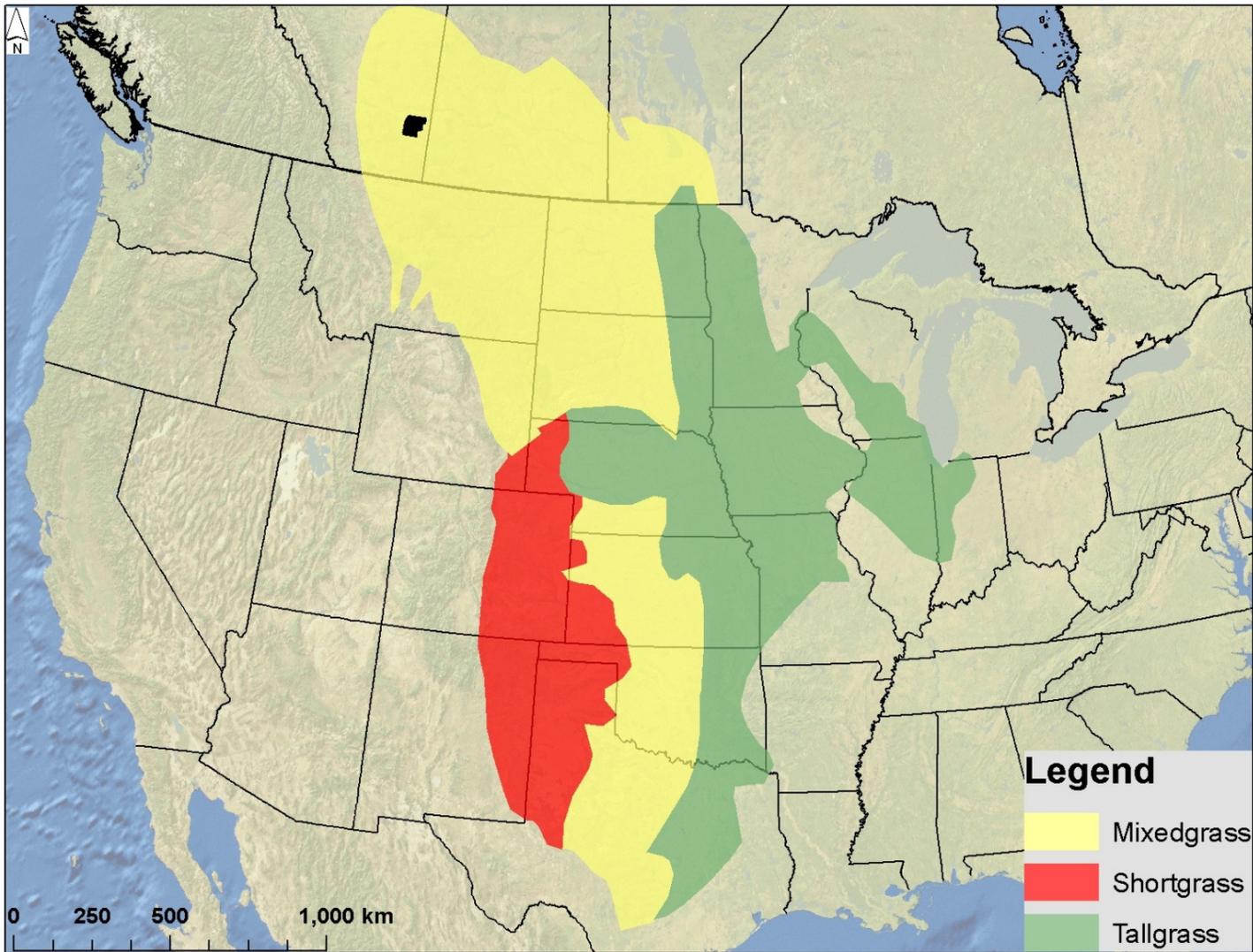


Figure 1.2: Ecoregions within the North American Great Plains; CFB Suffield in black (modified from Ford and McPherson 1997).

However, the removal of litter has been shown to increase soil temperatures (Vermiere et al. 2005) and evapotranspiration (Willms et al. 1993), which favour drought-tolerant C4 species (Smoliak et al. 1972).

Fire processes which induce succession in northern mixedgrass prairie may be directly related to the selective suppression of a species or functional group based on fire timing—particularly spring burns which suppress C3 species (Anderson et al. 1970; White and Currie 1983; Schact and Stubbendieck 1985; Redmann et al. 1993; Shay et al. 2001)—or indirectly by the removal of litter which conserves scarce moisture (Dix 1960; Redmann 1978; Willms et al. 1986; Dormaar and Willms 1990; Willms et al. 1993; Dormaar et al. 1994; Vermiere et al. 2005).

While restoring fire processes to rangeland ecosystems has been a recommended management tool, information on historical regimes is very limited, and experimental research which provides insight into the effects of fire in semi-arid regions, is important in determining management strategies (Scheintaub et al. 2009). Unfortunately, research of this nature has been traditionally difficult to pursue, due to the spatial constraints of intensive field-based observations. However, geospatial technologies such as remote sensing and geographic information systems (GIS) provide enhanced capacities for observing and analyzing ground phenomena across large geographic areas, and present new opportunities for rangeland fire-ecology research.

1.3 THE ROLE OF REMOTE-SENSING FOR MANAGEMENT OF RANGELANDS

Where traditional ground-based monitoring alone has limited capacity to detect change over time while simultaneously accounting for spatial variability, some rangeland vegetation parameters (e.g., vegetation cover, soil erosion, and changes in landscape composition and

configuration) can be monitored at large spatial and temporal scales using ecological indicators derived from satellite imagery (Washington-Allen et al. 2006). Remote sensing has been employed successfully in previous research to assess rangeland degradation (Geerken and Ilaiwi 2004), assess the ecological implications of cattle management (Hunt and Miyake 2006), and to understand the role of climate in rangeland dynamics (Paruelo and Lauenroth 1998). These studies suggest that remote sensing analysis has the potential to fill in gaps in the understanding of rangeland dynamics in relation to land use and natural variability.

The majority of previous remote-sensing studies examining rangelands have employed time series of imagery using multiple dates, known as multi-temporal image analysis. This approach is generally preferred, because sparse vegetation in rangelands reflects very limited amounts of radiation which can be detected by satellite sensors, confounding single image approaches based on spectral information only (Tueller 1987; Huete 1988). In contrast, multi-temporal image analysis may enable the elucidation of specific vegetation information not available by other methods (Lillesand et. al. 2008). Multi-temporal image analysis in rangelands exploits the phenological characteristics of vegetation to uncover temporal patterns in vegetation development that permits the discrimination of subtle vegetation communities that are often beyond the reach of single-date analysis procedures.

Phenology is the study of the timing of recurring biological events, and the causes of their timing with regard to biotic and abiotic forces (Lloyd 1990). Vegetation-phenological investigations are concerned with the influence of seasonally varying environmental conditions such as day-length, air temperature, and water availability on the timing of plant development (Lloyd 1990; deBeurs and Henebry 2004). Multi-temporal image analysis therefore attempts to

identify or differentiate phenological differences in vegetation through a time series of images, often via the analysis of vegetation indices (VIs; Lloyd 1990). Further, this analysis can be used to answer scientific questions relating to landscape disturbance, land cover and land cover change, human and climate change impacts, and drought (Huete et al. 1999).

VIs often form the basis for remote sensing-based phenological investigations (Huete et al. 2002). VIs have been closely linked to the chlorophyll content and photosynthetic activity of green vegetation (Huete et al. 1999; Huete et al. 2002) and are therefore particularly useful for studying vegetation health and function across time. Time-series data analyses have typically employed high-temporal-resolution imagery such as those from the 1000-m resolution Advanced Very High Resolution Radiometer (AVHRR) VI data to analyze vegetation phenology and dynamics (Justice et al. 1985; Townshend and Justice 1986; Justice et al. 1991; Loveland et al. 1991). However, with the advent of 250 m Moderate Resolution Imaging Spectroradiometer (MODIS) VI data, there is more potential for higher-spatial-resolution multi-temporal applications (Lunetta et al. 2006). While many other satellite sensors—including SPOT, IKONOS, Quickbird, and Landsat—have the capacity to derive VIs suitable for multi-temporal image analysis, they lack the high temporal resolution possessed by AVHRR, MODIS, Vegetation, and other such instruments typically preferred for this kind of research. As a result of its enhanced spatial resolution (relative to AVHRR) and the availability of sophisticated high-level data products (relative to Vegetation), MODIS VI products were chosen for use in this study, and will be the subject of the remaining sensor-specific comments appearing in this chapter.

The normalized difference vegetation index (NDVI) is a universal VI shared by most high-temporal-resolution sensors including MODIS, and is commonly used in multi-temporal studies (Huete et al. 1999). The index exploits the differential reflection of red and near-infrared light by green vegetation, wherein red light is absorbed and near-infrared light is reflected (Huete et al. 1999). Conceptually, the NDVI is derived as follows:

$$NDVI = (\rho_{NIR} - \rho_R) / (\rho_{NIR} + \rho_R) \quad (1-1)$$

where ρ_{NIR} is near infrared reflectance and ρ_R is red reflectance.

Since NDVI can suffer from the introduction of signal noise caused by background soil exposure (Elvidge and Lyon 1985; Huete et al. 1985; Heilman and Kress 1987; Huete and Warrick 1990) and also by atmospheric conditions (Huete and Liu 1994), the Enhanced Vegetation Index (EVI, collected by MODIS) has been developed to address these issues. Conceptually, the EVI is derived as follows:

$$EVI = 2 * (\rho_{NIR} - \rho_R) / (L + \rho_{NIR} + C1\rho_R + C2\rho_B) \quad (1-2)$$

where L is a canopy background adjustment term, and C1 and C2 weigh the use of the blue channel in aerosol correction of the red channel (Huete and Liu 1994).

As a monitoring tool of vegetation phenology, VIs can be used to construct seasonal and temporal profiles of vegetation activity, which permit comparisons between time periods. The temporal profile of the NDVI has been shown to depict seasonal and phenological activity, such as the length of the growing season, onset of greenness, and senescence, among others (Huete et al. 1999). Specific VI attributes which can be extracted from phenological profiles include but

are not limited to: start of growing season, end of growing season, integrated VI, and VI rates of change (Table 1.1).

In rangelands, multi-temporal image analysis via NDVI has been used successfully at the continent scale across the Great Plains (extending from Mexico to Canada) to differentiate major vegetation types (Ricotta et al. 2003). Further, multi-temporal analysis using NDVI has been used successfully at the ecosystem scale to discriminate between native and invaded species of semi-desert rangelands in Arizona (Huang et al. 2009). Finally, multi-temporal analysis using NDVI has also been used to quantify the spatial extent of plant functional types (PFTs) in South Dakota, by exploiting the differential rates of green-up of C3 and C4 functional grass types (Foody and Dash 2007).

Remote sensing of PFTs exploits asynchronous growth between C3 (cool season) grasses, and C4 (warm season) grasses, with a classification scheme between species-specific and broad vegetation types (Ustin and Gamon 2010). Davidson and Csillag (2003) explored this concept in Grasslands National Park, Saskatchewan (also located in mixedgrass prairie), and found that NDVI could be used to differentiate C3 and C4 species at coarse spatial scales (1000 m), but suggested further research aimed at identifying vegetation types at finer spatial scales, due to the sub-pixel mixing of vegetation types in coarse-resolution imagery.

Table 1.1: Phenology-related multi-temporal remote sensing metrics (modified from Hird 2008).

Metric	Description	Method of Estimation
Start of Growing Season (SOS)	Timing of photosynthesis at the start of measurable growth	Thresholds, inflection points, curve derivatives
End of Growing Season (EOS)	Timing of photosynthesis at the end of measurable growth	Thresholds, inflection points, curve derivatives
Length of Growing Season (LGS)	The duration of measurable photosynthesis, representing the length of the growing season	Number of composite periods or days between SOS and EOS
Integrated NDVI (iNDVI)	Overall productivity and biomass produced during the growing season	Area under the NDVI curve between SOS and EOS
Rate of Green-up	Speed at which spring green-up occurs	Slope of line between SOS and maximum NDVI
Green-Up iNDVI	Portion of total growing season productivity produced during green-up	Area under the NDVI curve between SOS and maximum NDVI, over iNDVI
Start of Senescence	Timing and level of photosynthesis at the start of rapid decrease in photosynthesis	Inflection point method
Rate of Senescence	Speed at which autumnal senescence occurs	Speed at which autumnal senescence occurs
Senescence iNDVI	Portion of total growing season productivity produced during senescence	Area under the NDVI curve between maximum NDVI and EOS, over iNDVI
Maximum NDVI	Timing and level of photosynthesis at maximum photosynthesis reached during the growing season	Maximum NDVI between SOS and EOS
Minimum NDVI	Timing and level of photosynthesis at minimum photosynthesis reached during the growing season	Minimum NDVI between SOS and EOS
Mean NDVI	Overall mean level of photosynthesis occurring throughout the year	Mean of NDVI values over a year

1.4 MODIS

MODIS is a moderate-spatial-resolution (250 to 1000 m), high-temporal-resolution (1-2 days), high-spectral-resolution (36 bands) sensor aboard the TERRA and AQUA satellites, commonly used in phenological studies. Data is provided free to the public from a variety of distribution portals (e.g., Land Processes Distribution Active Archive Centres/LP-DAAC, Warehouse Inventory Search Tool/WIST). MODIS is available in a variety of formats and processing levels, with specifications aimed at research into particular land and ocean processes. MODIS processing involves the refinement of raw digital numbers representing radiance, into progressively more complex indices and biophysical parameters.

1.4.1 MODIS Processing Levels

In addition to specific data disciplines, MODIS is distributed in a number of processing levels (Huete et al. 1999), including unprocessed radiance (Level 0/L0), top-of-atmosphere (TOA) reflectance (L1), surface reflectance (L2), vegetation indices by temporal compositing (L3), and various biophysical parameters (L4). A key issue with respect to the data acquired by MODIS is the influence (and variance) of external noise, including atmospheric effects, cloud and shadow, and sun-sensor-surface geometries (Huete et al. 2002). While L2 data have been ‘corrected’ to account for atmospheric effects, it is still subject to variance in sun-sensor-surface geometry (bidirectional reflectance distribution) and cloud cover (Huete et al. 2002). Thus, the primary aim of L3 data products is to remove these effects through temporal compositing (Huete et al. 1999), which attempts to mask cloud-affected pixels, and re-populate them through automated algorithms, using available pixels from other acquisition dates in a defined time

period (i.e.: 16 days). Bidirectional reflectance distribution function algorithms are also applied to L3 data products, to account for differences in sun-sensor-surface geometries (Huete et al. 1999). However, despite all of the processing steps designed to increase the data reliability and utility of high-level products, MODIS data is still significantly affected by variability in atmospheric conditions and sun-sensor-surface viewing geometries (Hird and McDermid 2009), requiring further processing.

1.4.2 Noise Processing and Signal Loss

In order to reduce noise caused by external factors, additional noise-reduction algorithms can be applied to VI time series data which seek to detect the desired, low-frequency signal that corresponds with vegetation phenology, while minimizing or removing the undesirable, high-frequency noise completely unrelated to phenology (van Dijk et al. 1987).

Noise-reduction approaches typically fit into one of two categories: function-fitting or filtering (Hird 2008). Function-fitting noise reduction involves the construction of a new NDVI time series that is fitted to the overall trends in the original profile that can be described using a function (Hird 2008). In contrast, filters aim to minimize the high-frequency noise while retaining the desired low-frequency information in the times series, often incorporating more of the original data in their result (Hird and McDermid 2009). However, the results of filters are not generally as smooth as those produced through function-fitting algorithms (van Dijk et al. 1987).

Of particular interest to rangeland-vegetation studies (such as the ones pursued in this research) are the various impacts of noise-reduction strategies on smoothed VI time series. For

example, blue grama (*Bouteloua gracilis* [Willd. Ex Kunth] Lag. Ex Griffiths)—the primary C4 species in the study area (Smith 2010)—displays erratic seasonal biomass production curves rather than parabolic curves that characterize other species (Turner and Klipple, 1952; Benment, 1969). As a result, the physiology of this species must be carefully considered when applying noise reduction; temporal smoothing by function-fitting may be inappropriate for a species which does not have predictable parabolic growth. The results of the PFT classification for this project must be sufficiently accurate to detect changes in vegetation resulting from land use. As such, temporal smoothing is critical in reducing extraneous noise and preserving phenological signals, in order to detect ecological changes which arise from land use at CFB Suffield.

1.5 CANADIAN FORCES BASE SUFFIELD

CFB Suffield is located within the dry mixedgrass subregion of Alberta (Strong and Leggat 1992; Fig 1.3). The area which now comprises CFB Suffield was used historically for cattle ranching from the 1880s to 1909, when the land was homesteaded. However, due to the limited productivity within the dry mixedgrass subregion, poor soil quality and resulting poor crop yield, many homesteaders quickly relocated. Out of 2385 resident families which occupied the lands in the district in 1922, only 645 remained just four years later. Dau (1983) argued that the dry land farming techniques used during that time were inadequate for the region's soils and climate, and that the moisture and organic matter within cultivated fields were entirely depleted in less than 20 years. Farms were consolidated until more than 38 % of the Military Training Area was held under individual title (Norbeck 1972).

In addition to agriculture, CFB Suffield was important for ecological conservation because of its native prairie land cover. In 1922, 140 km² of lands now occupied by the CFB Suffield National Wildlife Area (Fig 1.3) were established as Wawaskesy National Park, by a federal Order-in-Council to protect pronghorn antelope from extinction. The park was closed in 1938 upon the stabilization of the pronghorn population.

In 1941, CFB Suffield lands were jointly obtained by the Canadian and British governments for military defence research. Land acquisition was relatively easy since a large portion of the land was never homesteaded, and over 55 % of the area was already abandoned (Dau 1983). During World War II, experiments and field trials of chemical weapons were carried out. Research also included significant explosive trials, capped off with one of the world's largest non-nuclear detonations (500 tonnes of TNT) in 1964 (Dau 1983).

In addition to military training, land use agreements permitting cattle grazing and oil and gas development at CFB Suffield were also signed by the Department of National Defence. Cattle grazing was originally introduced in the 1960s to afford emergency grazing opportunities as a result of drought, and became formalized in the 1980s under the management of the federal Prairie Farm Rehabilitation Administration (PFRA). In 1975 and 1977, agreements were signed between the governments of Alberta and Canada for the development of hydrocarbon resources and the establishment of the Oil Access Area (Fig 1.3), where above-ground infrastructure permits the exploration of oil deposits in the northwest corner of CFB Suffield. The agreement also created the provincial crown corporation known as Alberta Energy Company (AEC; now known as Cenovus), responsible for the development of oil and gas resources across the entirety of CFB Suffield (Dillon Consulting 2006).

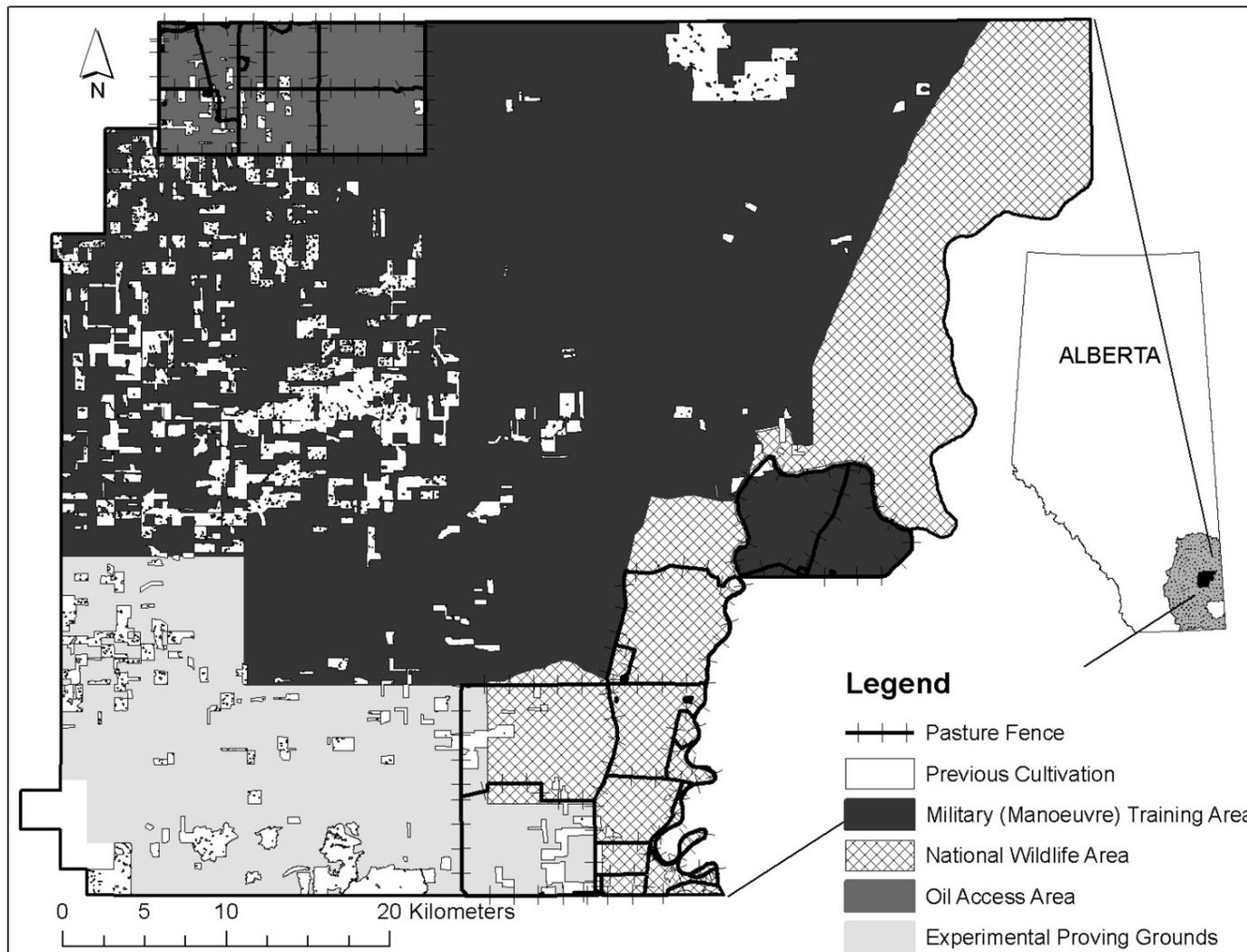


Figure 1.3: Historical and current land use at CFB Suffield (inset: grey stipple = dry mixedgrass subregion of Alberta).

Given the multitude of land uses at CFB Suffield, there is significant potential for ecological degradation associated with disturbance (Dau 1983); some environmental changes have been monitored since the 1970s, by both ground-based assessment and by remote-sensing techniques (Jacques 1981).

1.6 RANGELAND SUCCESSION AT CFB SUFFIELD

Ecological succession is an important process to study, because it provides a framework for understanding changes in ecosystem status including biodiversity and productivity (Glenn-Lewis and van der Maarel 1992), and ecosystem resistance and resilience to change (Stringham et al. 2003). Further, the identification of seral states and thresholds enables the identification of management objectives (Bestelmeyer 2006). In order to understand ecological changes resulting from land use, long-term ground-based monitoring of vegetation and land use has been carried out at CFB Suffield since 1993 (Smith 2010). A total of 650 transects, stratified across range sites, have been established where species' canopy cover is measured within 15 0.1 m² quadrats once every five years. Using these observations, vegetation-community changes have been revealed by ordination methods, wherein relatively undisturbed/ reference states (C3 dominant communities) retrogress to C4 dominant communities with increasing levels of land use disturbance. In work related to the research reported in this thesis, I used detrended correspondence analysis (DCA, McCune and Grace 2002) to identify environmental and land use gradients for three separate ecological sites occurring within the Base: Loamy (associated with morainal landforms, and includes loam, silt loam, silt, clay loam, sandy clay loam, and silty clay loam soils), Sands (associated with glaciofluvial or low relief eolian landforms, and includes loamy sand and sand soils), and Blowouts (hardpan and solonetzic pits usually spatially co-

occurring with Loamy sites; Alberta Sustainable Resource Development 2010). DCA is an appropriate method of identifying environmental and land use gradients in relation to species composition (McCune and Grace 2002). This analysis assumes that changes in species' presence or abundance are driven primarily by unidentified multi-dimensional environmental gradients, which can be detected by the correlation of derived gradients with species' attributes and land use or environmental metrics (McCune and Grace 2002).

Environmental and land use gradients were identified by DCA axes, based on species' canopy cover, and environmental and land use variables (Smith 2010). Based on this analysis, two attributes of fire were deemed ecologically significant: (i) total number of fires, and (ii) time since last fire. The total number of fires (interpreted as a gradient of fire-induced succession) is well-correlated with axes 1 and 2 for Blowouts ($r = -.40$, $r = -.49$) and Loamy ($r = -.23$, $r = -.45$), but less so for Sands range sites ($r = -.20$, $r = -.12$; Table 1.2). However, time since last fire (interpreted as a gradient of recovery from fire) is well-correlated with axis 1 for Sands ($r = .33$), but no meaningful relationship exists for Loamy or Blowouts range sites.

Critically, species' cover values are well-correlated with the same axes. The direction of the relationship between species' cover is also important: blue grama (a C4 species) is negatively correlated with axes relating to fire, while western wheatgrass (*Pascopyrum smithii* [Rybd.] A. Löve; a C3 species) is positively with axes relating to fire. While fire appears to be an important land use factor correlated with DCA axes 1 and 2, environmental variables also correlate with derived axes. Slope is correlated with axis 2 for Loamy ($r = .30$), while topographic position is correlated with axis 3 for Sands ($r = .28$; Table 1.2). The results of this work suggest that fire is related to changes in plant functional diversity (the critical component of range health assessment), with different functional groups (C3 and C4 species) displaying differential

responses to fire. Moreover, ordination reveals that topographic position and slope are also important variables in explaining species composition.

Table 1.2: Results of linear correlation of species'/plant functional type (PFT) canopy cover and environmental variables with DCA axes.

Factor (photosynthesis)	Blowouts (n=29)			Loamy (n=95)			Sands (n=86)		
	Axis 1	Axis 2	Axis 3	Axis 1	Axis 2	Axis 3	Axis 1	Axis 2	Axis 3
blue grama (C4)	-0.54	0.41	-0.40	-0.78	-0.08	0.35	-0.49	0.45	0.09
needle and thread (C3)	-0.57	0.18	0.21	-0.17	-0.28	-0.12	-0.28	-0.48	-0.50
northern wheatgrass (C3)	0.01	-0.65	-0.04	0.22	0.36	0.52	0.49	-0.42	0.06
western wheatgrass (C3)	0.80	0.40	0.18	0.65	-0.28	-0.48	-0.13	0.30	0.42
soil texture	-0.16	-0.07	-0.03	-0.09	-0.06	0.04	-0.05	-0.09	0.29
topographic position	0.05	-0.22	-0.10	0.12	0.05	0.09	0.17	-0.14	0.28
bare soil	-0.16	-0.07	0.26	-0.10	-0.20	-0.08	-0.24	0.01	0.01
litter biomass	0.21	0.09	-0.34	0.23	0.05	0.12	0.25	-0.08	-0.02
moss cover	-0.16	-0.15	0.02	-0.30	-0.05	0.00	-0.17	0.08	0.15
aspect	-0.10	-0.14	-0.01	-0.08	-0.03	-0.11	-0.11	0.08	-0.13
slope	-0.12	0.15	-0.21	-0.08	-0.30	0.20	0.09	0.06	-0.23
total fires	-0.40	-0.49	-0.18	-0.23	-0.45	0.07	-0.20	-0.12	0.11
time since last fire	-0.02	0.12	0.15	0.17	0.17	0.14	0.33	-0.19	0.07

However, it must be noted that while fire appears to be an ecologically important disturbance, this type of field-based data collection and analysis cannot directly quantify the relationship between fire and species composition, nor separate land-use gradients (*the signal*) from environmental gradients (*the noise*), nor identify specific thresholds of change. Thus, landscape-level research which directly quantifies the relationship between fire and the presence of PFTs, and also controls for natural variability and other land use, is required to expand the current level of ecological understanding.

1.7 RESEARCH OBJECTIVES

The primary goal of the research reported in this thesis was to develop novel strategies for mapping grassland-vegetation communities through multi-temporal remote sensing, thereby enabling a procedure for conducting landscape-level assessments of ecosystem health in relation to land use at CFB Suffield. In contrast to previous PFT studies which were limited to determining the utility, accuracy, and spatial extent of PFT classifications, this project was designed to establish both the *observed* ecosystem state, through PFT mapping, and the *expected* ecosystem state, through the incorporation of ecological theory and spatial data used to define reference ecosystem states via *ecological site descriptions*. Further, this project was also designed to identify causal factors, by relating differences (*observed – expected*) in ecosystem states to specific land-use factors (fire).

The specific research objectives of this project were:

1. To establish the capacity of multi-temporal time series of MODIS VI data to differentiate between C3 and C4 PFTs at CFB Suffield, and test the performance of novel multi-temporal processing strategies in the production of a fully ground-truthed PFT map. If a suitable technique for mapping PFTs can be established, I can—for the first time—map the distribution of PFTs in relation to their expected state, and directly quantify the most important component of range health—plant functional diversity; and
2. To establish a relationship between PFT maps and fire history, and explore the effect of repeated fire across different range sites at CFB Suffield. If a relationship between PFTs and fire history can be established, I can—for the first time—examine fire-related ecology across multiple decades and range site types, which has previously been logistically impossible. This

will be achieved by comparing contemporary ecosystem states relative to their complete historical fire regimes, which span several decades.

In order to achieve these objectives, a series of questions and hypotheses were formulated (Table 1.3), relevant datasets were collated, data processing and workflows were established (Fig 1.4), and appropriate statistical tests were carried out. Project questions, hypotheses, and associated analyses are described in more detail below.

With respect to PFT classification (Objective 1), the effect of temporal filtering was explored to determine the most effective noise reduction approach, given the problematic physiology of blue grama. Secondly, several VI metrics were explored to determine the most effective approach to differentiating PFTs. Finally, ecologically relevant data (topography and soils, identified as important gradients in this chapter) were incorporated into PFT multinomial logistic regression classifications, with the aim of controlling natural variability and producing an accurate PFT map.

With respect to fire ecology investigations (Objective 2), fire history was manually digitized from the Landsat archive and a corresponding spatial database was established to enable statistical modelling (via probit regression) between the ecosystem states derived by PFT classification, and their corresponding fire history. Further, two fire ecology hypotheses were tested: (i) C4 grass species would replace C3 grass species with increasing fire and that succession processes would be similar across range sites; (ii) intra-year fire timing was not a primary factor in driving succession from C3 to C4 species. Finally, the processes of retrogression and progressive succession were explored using X^2 tests between the proportion of PFTs in 'burned' treatments compared to the proportion of PFTs in 'rest' treatments, in order to assess the resilience and resistance of different range sites.

Table 1.3: Research objectives, questions, data sources, and data processing.

Project Steps	Questions/Hypotheses	Datasets (timelines)	Data Processing
Plant Functional Type (PFT) Classification	What is the effect of temporal filtering on PFT classification model performance in northern dry mixedgrass prairie?	MODIS NDVI (2001 to 2011)	Temporal filtering (4253H-twice filter)
	What phenological metrics work best in northern dry mixedgrass prairie?	MODIS NDVI (2001 to 2011)	Derivation of relative-rate-of-change, iVI
	Range site (soils) data meaningfully contributes to PFT classification models	Soil polygons	a. Conversion from polygon to raster b. Integration of soils data into PFT logistic regression model
	Topographic data (solar insolation as a proxy) meaningfully contributes to PFT classification models	Digital Elevation Model (DEM)	a. Derivation of solar insolation raster b. Integration of solar insolation into PFT logistic regression model
Rangeland Fire Ecology	What is the fire history at CFB Suffield?	Landsat (1972 to 2007)	a. Geo-rectification, Tasseled Cap transformation, Normalized Burn Ratio

Project Steps	Questions/Hypotheses	Datasets (timelines)	Data Processing
			<p>b. Manual delineation of annual fire scars</p> <p>c. Tabulation of complete fire history</p>
<p>Rangeland Fire Ecology</p>	<p>Fire induces succession in northern dry mixedgrass prairie, from C3 to C4 species and there are no differences in succession between range sites</p> <p>How do successional and recovery processes operate in northern dry mixedgrass prairie; are they different between range sites?</p> <p>Fire timing is not a factor in succession from C3 to C4 species in northern dry mixedgrass prairie</p>	<p>MODIS PFT classification, soil data, complete fire history</p> <p>MODIS PFT classification, range site data, complete fire history</p> <p>MODIS Monthly Burned Area Product (2001 to 2009)</p>	<p>Probit regression between number of PFT pixels and total fires</p> <p>X² tests of PFT pixels between burned and recovery treatments</p> <p>a. Tabulation of burn pixels by month by year</p> <p>b. T-tests of total burned area between spring (May-June) and summer (July-Sept)</p>

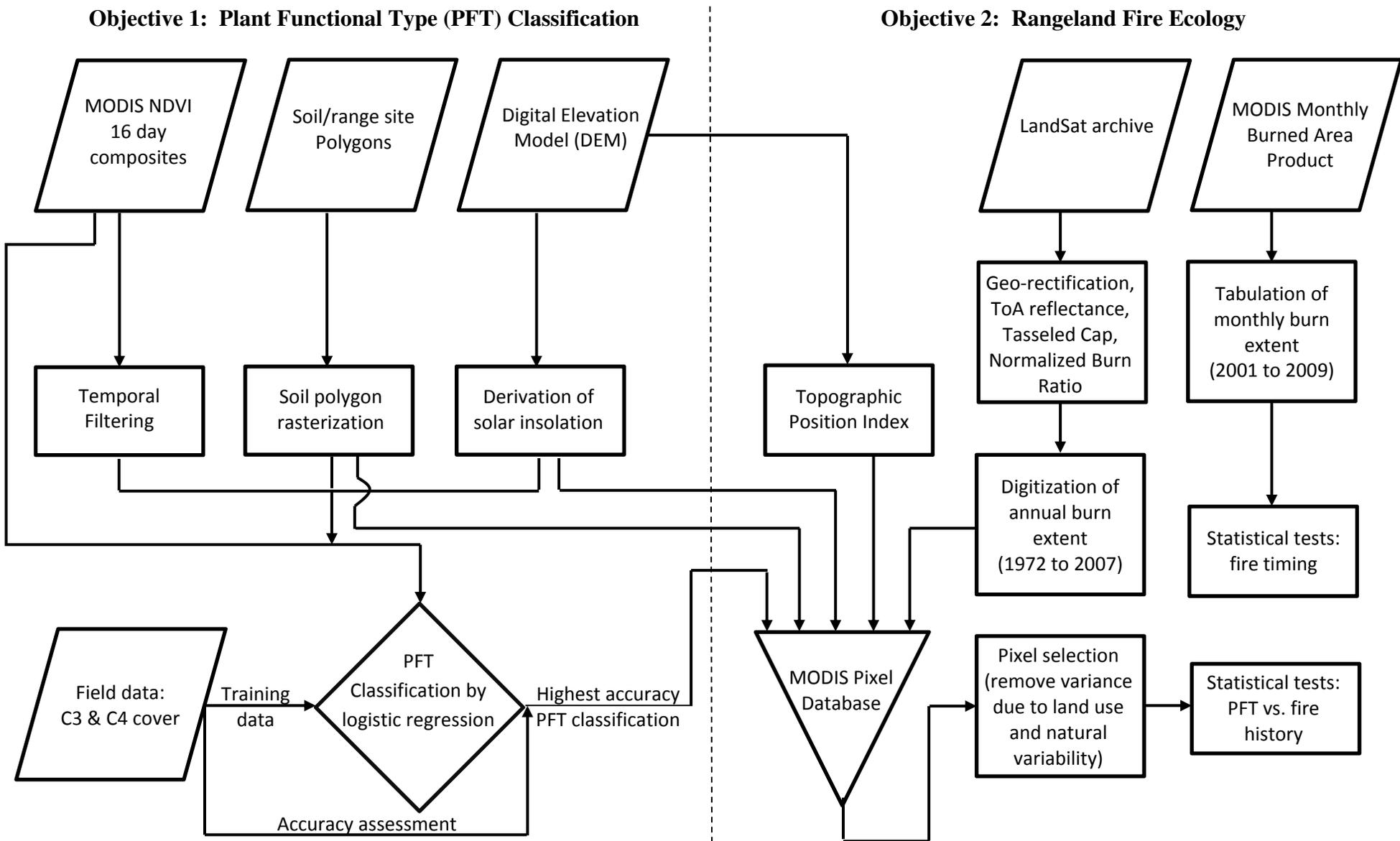


Figure 1.4: Project workflow to achieve objectives.

1.8 ORGANIZATION OF THESIS

This first chapter introduces the concepts of range ecology, health, and ground-based monitoring, fire ecology, and the role of multi-temporal remote sensing in rangeland management, describes the study area, and provides an overview of the specific research objectives to be addressed in this thesis, including the development of an accurate multi-temporal PFT classification, and the use of the multi-temporal PFT classification to understand fire ecology in northern dry mixedgrass prairie. The pursuit of these objectives is presented in two self-contained research articles that fit together to examine rangeland fire ecology in novel ways.

Chapter 2 investigates the specific ecology of northern dry mixedgrass prairie, examines the effect of temporal smoothing on the phenological characteristics of functional types in the study area, and incorporates ecologically-relevant spatial variables, with the aim of developing an accurate PFT classification (Objective 1).

Chapter 3 builds upon existing field-based research of rangeland succession, by establishing robust landscape-level statistical relationships between ecosystem states derived by PFT classification and inter-year fire history digitized from the Landsat archive, and determining whether intra-year fire timing from MODIS burned area data was related to succession (Objective 2).

Chapter 4 summarizes the conclusions of this work, outlines the main contributions to remote-sensing and rangeland ecology, and provides suggestions for future research.

CHAPTER 2: PLANT FUNCTIONAL TYPE CLASSIFICATION USING MODIS, TEMPORAL FILTERING, AND ECOLOGICAL VARIABLES WITHIN THE DRY MIXEDGRASS SUBREGION OF ALBERTA

2.1 ABSTRACT

Plant functional type (PFT) grassland classification by remote sensing relies on the asynchronous growth of cool-season grasses (C3 photosynthesis), and warm-season grasses (C4 photosynthesis). However, C4 species in northern mixedgrass prairie respond rapidly to short-term environmental variability, resulting in erratic growth profiles. Because of the common need for smoothing of time-series data, C4 multi-temporal profiles in northern mixedgrass prairie may be inadvertently degraded by standard pre-processing routines. In this chapter, relationships between MODIS-derived vegetation index (VI) attributes, ecologically relevant spatial variables, and temporal filtering were explored within the context of mapping PFTs across Canadian Forces Base Suffield in southeastern Alberta. The best predictive model (overall accuracy = 74 %, weighted kappa = 0.53) used filtered NDVI from 7 composite periods, solar insolation, and soil texture (percent sand fraction) as inputs. Results indicate that the C4 species do indeed display erratic phenological profiles, thereby confounding many routine attempts to reduce noise in MODIS composite algorithms. However, temporal filtering remains an appropriate noise-suppression technique enabling the separation of PFTs in this ecoregion.

2.2 INTRODUCTION

Broad-scale multi-temporal image analysis via vegetation indices (VIs) can be used to exploit phenological differences in vegetation growth, in order to elucidate spatial patterns of vegetation distribution (Adjorlolo et al. 2012). The concept of plant functional type (PFT) uses structural, physiological, or phenological characteristics to group species in predictable responses to environmental conditions or disturbance (Gitay and Noble 1997; Lavorel et al. 1997; Shugart 1997; Tilman et al. 1997; Hooper and Vitousek 1997). Multi-temporal image analysis has been successfully employed in North American rangelands to differentiate PFTs which, as a result of differences in their photosynthetic pathways, can be separated by their asynchronous growth (Goodin and Henebry 1997; Davidson and Csillag 2001, 2003; Ricotta et al. 2003; Foody and Dash 2007, 2010). Remote sensing of PFTs exploits the phenological differences between C3 (cool season) grasses, and C4 (warm season) grasses, with a classification scheme that falls midway between species-specific and broad vegetation types (Ustin and Gamon 2010). Species which employ the C3 photosynthetic pathway are generally less well adapted to conditions of high light (Tieszen 1970), high temperature (Schuster & Monson 1990), and low soil moisture (Barnes et al. 1983) than are species which use the C4 photosynthetic pathway. A remote-sensing approach designed to exploit phenological differences between PFTs is relevant in answering a variety of ecological questions (Adjorlolo et al. 2012), including land-use effects on ecosystem function (Tiezen et al. 1997), and ecosystem change as a result of environmental change including climate (Ehlinger et al. 1997; Davidson and Csillag 2001).

In grasslands, multi-temporal image analysis via the normalized difference vegetation index (NDVI) has been used at different spatial scales: at the continent scale to differentiate

vegetation types occurring across the Great Plains (Ricotta et al. 2003), and at the ecosystem scale to quantify the spatial extent of different community types in South Dakota (Foody and Dash 2007), and at the local scale to map PFTs in Grasslands National Park, Saskatchewan (Davison and Csillag 2003). However, these investigations have revealed some limitations of PFT-based remote sensing classifications. First, the relationship between PFT and remote-sensing variables changes with spatial scale (Davidson and Csillag 2001). Secondly, PFT classifications created in one study area may have limited application to other regions (Foody and Dash 2010) due to their empirical nature. Furthermore, while fine-spatial-resolution imagery may provide better PFT classification results, its use is impractical in mapping large areas. This contrasts with large-area mapping by coarse-resolution imagery, where the mixing of remote-sensing responses from heterogeneous regions reduces the potential to accurately map PFTs (Foody and Dash 2007). Finally, the application of remote-sensing based PFT classification remains limited, particularly because an ecological framework for understanding vegetation function has not been established by either ecologists or remote-sensing practitioners (Ustin and Gamon, 2010). The incorporation of other relevant ecological variables including solar radiation patterns, wetness gradients, and topographic elements may improve PFT classification performance (Adjorlolo et al. 2012). Indeed, vegetation patterns have been shown to strongly correlate with solar radiation models (Fu and Rich 2002), and similarly, vegetation patterns correlate with topographic position in mixedgrass prairie (Phillips et al. 2012).

In addition to the challenges identified above, another major problem in the use of multi-temporal VI data is the signal loss or degradation resulting from atmospheric conditions in a time-series of images (Gutman 1991; Viovy et al. 1992; Huete et al. 1999). In order to reduce this radiometric noise, additional noise-reduction algorithms designed to separate the low-

frequency signal corresponding to vegetation phenology from high-frequency noise are commonly applied (Hird 2008). Noise-reduction approaches for PFT classifications typically fall into two general categories: function-fitting algorithms, including splines (Hermance et al. 2007) or filtering, including moving averages (Davidson and Csillag 2003). In general, the results of filters are not as smooth as those produced through function-fitting algorithms (van Dijk et al. 1987; Hird and McDermid 2009). Thus, the choice of temporal-smoothing approaches must be carefully considered in the context of larger methodological objectives. In the case of PFT classification, for example, the application of smoothing algorithms might suppress the true phenological characteristics of C4 species, which are present in northern mixedgrass prairie (Davidson and Csillag 2003).

2.2.1 Northern Dry Mixedgrass Prairie Ecology – Effects on Multi-temporal Phenological Profiles

Weather factors of precipitation, temperature, humidity, evaporation, solar radiation and wind, coupled with topography and elevation, influence local micro-climatic regimes, resulting in micro-environmental complexes of rangelands (Whitman and Wolters 1967). Plant communities within the northern dry mixedgrass subregion are dominated by cool-season (C3) grass species, well adapted for early season growth during cool, wet conditions (Coupland 1950; Adams et al. 2005). The predominant C3 grasses by canopy cover are needle and thread (*Hesperostipa comata* [Trin. & Rupr.] Barkworth), western wheatgrass (*Pascopyrum smithii* [Rybd.] A. Löve), and northern wheatgrass (*Agropyron dasystachyum* [Hook.] Scribn.), with blue grama (*Bouteloua gracilis* [Willd. Ex Kunth] Lag. Ex Griffiths) as the primary C4 species (Adams et al. 2005). C4 species in northern dry mixedgrass prairie occur in the northern extent

of their range, existing under marginal conditions for growth, and are highly responsive to subtle changes in environmental conditions (Davidson and Csillag 2003); blue grama initiates growth only when the 10-day moving average soil temperature of the upper 15 cm exceeds 10.5 C (Detling et al. 1978). Once growth is initiated, blue grama has the ability to respond rapidly to rainfall events, resulting in erratic seasonal biomass production curves rather than parabolic curves that characterize other species (Turner and Klipple, 1952; Benment, 1969).

The overall objective of this study was to develop an accurate predictive model to locally estimate the ratio of canopy cover between C3 and C4 species in the dry mixedgrass subregion of Alberta, Canada by using multiple logistic regression of MODIS 16 day 250 m NDVI and EVI phenological attributes, ecologically relevant spatial variables, and temporal filtering. The results of this study are intended to form the basis of investigation into fire ecology in the next chapter.

2.3 DATA AND METHODS

2.3.1 Study Area

Canadian Forces Base (CFB) Suffield—110° E, 50° N—is situated within the Northern Great Plains of North America, within the dry mixedgrass subregion of the Alberta (Strong and Leggat 1992; Fig 2.1). Covering 2690 km², the base is comprised of a mix of unbroken prairie grasslands and remnant cultivation, where the land was ploughed prior to the establishment of the Base in 1971. Mean annual precipitation for this region is 272 mm, with a mean summer temperature of 16.2° C (Strong and Leggat 1992). Land uses in the study area include military training, military defence research, oil and gas development, and cattle grazing. The predominant ecological units (range sites) subject to ongoing land use include Loamy (30 % of

study area; typically associated with morainal landforms, and includes loam, silt loam, silt, clay loam, sandy clay loam, and silty clay loam soils), Sands (20 %; typically associated with glaciofluvial or low relief eolian landforms, and includes loamy sand and sand soils), and Blowouts (5 %; hardpan and solonetzic pits usually co-occurring with Loamy sites; Alberta Sustainable Resource Development 2010).

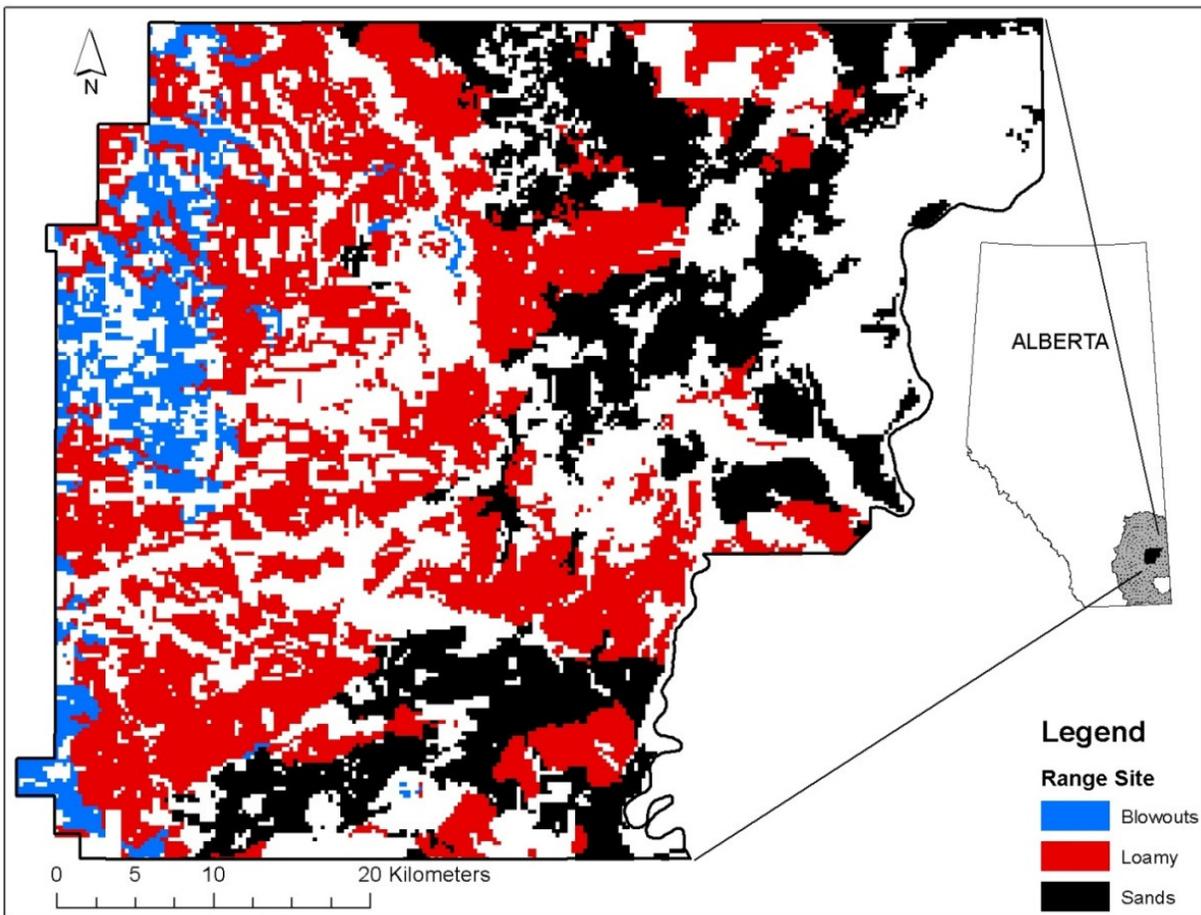


Figure 2.1: CFB Suffield and selected range sites (inset: grey stipple = dry mixedgrass subregion of Alberta).

By long-term monitoring of vegetation and land use at CFB Suffield, species compositional changes have been revealed by ordination methods, where relatively undisturbed/reference states (C3 dominant communities) transition to C4 dominant communities (blue grama), with increasing fire (Smith 2010). These changes can be represented by simple state and transition models, which represent ecosystem states and the disturbances which give rise to them (Stringham et al. 2003; Fig 2.2). However, while fire is an important factor in explaining community composition correlated with ordination axes, topography ($-0.10 < r < 0.28$), and soil texture ($-0.03 < r < 0.29$) are also important environmental variables correlated with ordination axes (Smith 2010).

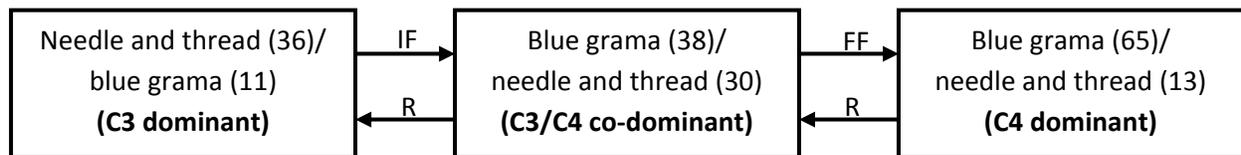


Figure 2.2: State and transition model of fire-induced succession on Loamy range site, IF = infrequent fire, F = frequent fire, R = rest from fire; species' mean canopy cover in brackets.

Understanding the above ecological considerations is critical in applying a PFT-related classification. Natural variation due range site and topography, in addition to erratic growth profiles of C4 species pose significant problems for a PFT classification in northern dry mixedgrass prairie. The challenge of multi-temporal separation by asynchronous growth between C3 and C4 species in this study area may be aided by:

1. the incorporation of topographic and range site attributes, which may reduce environmental variance associated with species' cover (Adjorlolo et al. 2012);

2. the derivation of rate-of-change values between VI composite periods, which reveal pronounced changes in photosynthesis, because C4 species in the study area are highly responsive to environmental change (Davidson and Csillag 2003); and
3. VI noise filtering, which may be the only appropriate method of noise reduction, because it does not force a temporal profile to fit a pre-determined function, particularly when the C4 species of interest (blue grama) has no characteristic phenological profile (Turner and Klipple, 1952; Benment 1969). Such filtering has the potential to reduce extraneous noise common in MODIS data, while preserving original phenological characteristics of the C4 species of interest.

2.3.2 MODIS and Signal Processing

Moderate Resolution Imaging Spectroradiometer (MODIS) is a moderate-spatial-resolution (250 to 1000 m), high-temporal-resolution (1-2 days), high-spectral-resolution (36 bands) sensor aboard the TERRA and AQUA satellites. Data from these sensors is distributed in a number of processing levels; from unprocessed radiance (Level 0/L0), top-of-atmosphere (TOA) reflectance (L1), surface reflectance (L2), vegetation indices by temporal compositing (L3), to the estimation of biophysical parameters (L4). However, even with all of the processing steps to increase data reliability and utility, MODIS data is still significantly affected by atmospheric conditions (e.g., cloud) and sun-sensor-surface viewing geometries (Huete et al. 1999, 2002). The two primary VIs used for multi-temporal investigation are the normalized difference vegetation index (NDVI) and enhanced vegetation index (EVI), which have been shown to represent photosynthetically active vegetation (Huete et al. 1999).

The NDVI is derived as follows:

$$\text{NDVI} = (\rho_{\text{NIR}} - \rho_{\text{R}}) / (\rho_{\text{NIR}} + \rho_{\text{R}}) \quad (2-1)$$

where ρ_{NIR} is near infrared reflectance and ρ_{R} is red reflectance

Since NDVI can suffer from the introduction of signal noise caused by background soil exposure (Elvidge and Lyon 1985; Huete et al. 1985; Heilman and Kress 1987; Huete and Warrick 1990) and also by atmospheric conditions (Huete and Liu 1994), the enhanced vegetation index (EVI) has been developed to address these issues.

EVI is derived as follows:

$$\text{EVI} = 2 * (\rho_{\text{NIR}} - \rho_{\text{R}}) / (L + \rho_{\text{NIR}} + C1\rho_{\text{R}} + C2\rho_{\text{B}}) \quad (2-2)$$

where L is a canopy background adjustment term, and C1 and C2 weigh the use of the blue channel in aerosol correction of the red channel (Huete and Liu 1994).

MODIS 250 m 16-day composite (MOD13Q1, L3) NDVI and EVI data were downloaded from 1 Jan 2001 to 31 Dec 2011 via the MODIS Land Processes Data Archive Centre (LP DAAC, 2005) which distributes the data at no cost. The study area comprises 2 MODIS scenes: 10v3 and 11v3, which were mosaicked to provide complete spatial coverage. VI data was re-projected to NAD83 UTM zone 12.

Upon visual assessment of MODIS data quality using a three class system (high: little degradation or noise in the image; more than 70 % of image pixels are usable; fair: some degradation or noise in the image, 50-70 % of image pixels are usable; and poor: high degree of degradation or noise in the image; 0 to 50 % of image pixels are usable; Table 2.1), it was apparent that smoothing was required before any further analysis could be carried out.

Table 2.1: Visual assessment of MODIS data quality for study area.

Year	Day of Year (DOY)																						
	0	0	0	0	0	0	0	1	1	1	1	1	1	2	2	2	2	2	3	3	3	3	
	0	1	3	4	6	8	9	1	2	4	6	7	9	0	2	4	5	7	8	0	2	3	5
	1	7	3	9	5	1	7	3	9	5	1	7	3	9	5	1	7	3	9	5	1	7	3
2001	P	P	P	P	H	H	F	F	F	F	F	F	F	H	H	H	H	H	P	F	P	P	P
2002	F	F	F	P	P	P	H	H	H	F	H	H	F	H	H	F	H	F	H	H	H	F	H
2003	H	P	F	F	H	H	F	P	H	H	F	H	H	F	F	F	H	H	F	P	P	P	P
2004	P	P	F	F	F	H	H	H	H	H	F	H	H	H	H	H	F	H	F	N	F	F	P
2005	P	P	F	H	H	H	H	H	H	F	F	F	F	P	H	H	H	F	H	F	H	P	P
2006	P	P	F	P	P	P	N	H	H	H	F	F	H	H	H	H	H	H	H	P	F	P	P
2007	F	F	P	P	F	H	F	H	H	H	H	F	F	F	F	F	F	H	H	F	F	P	P
2008	P	P	P	P	P	H	H	P	F	P	P	F	F	H	H	H	H	H	F	F	P	P	P
2009	P	P	F	P	P	P	H	H	H	H	P	H	F	H	F	H	H	P	F	F	P	P	P
2010	F	P	P	P	F	H	F	P	P	F	H	F	F	P	H	H	P	F	F	F	P	P	P
2011	H	P	P	F	P	F	P	H	H	H	F	P	F	F	F	H	H	H	H	H	F	P	P

H = high, F = fair, P = poor, N = image unavailable; growing season: DOY 97 to 305

In order to suppress undesired noise and retain the original signal profile, the 4253H-twice filter (Velleman 1980) recommended by Hird and McDermid (2009) was used to smooth VI profiles from the source data. Based upon data quality and temporal proximity to field data (2010-2012), VI data from 2009 was selected for use in PFT classification. The 4253H-twice filter applies a series of running median filters with windows of four, two, five and three, followed by a running weighted mean filter to a VI time series. The residuals of the filtering are then also filtered in this manner and then re-added to the filtered data (Hird and McDermid 2009).

Smoothing was undertaken by two different approaches: smoothing within a single year (2009), where due to the larger median filter spans, VI data nearest to the middle of the temporal dataset receives the most smoothing; Table 2.2); and smoothing across the entire span of images (2001 to 2011), where smoothing is applied equally to all 2009 images. Smoothing of MODIS

VI datasets was employed using ENVI 5.0 (Exelis Visual Information Solutions 2012) and the filtering algorithm developed by Hird (2008). VI data from day of year (DOY) 97 to DOY 305 were deemed to be the composite periods representing the growing season and were subsetted after filtering, for use in PFT classifications. Additional attributes were derived from the original VI data, including VI relative rate of change, where:

$$DVDT = (VI \text{ date } 2 - VI \text{ date } 1) / VI \text{ date } 2 \quad (2-3)$$

This derived rate of change index corresponds with the rate of green-up or senescence (Hird 2008), which may enable the separation of C4 species (which green up rapidly in response to weather) from C3 species.

Further, integrated VI (area under the growth curve), was derived, where:

$$iVI = \sum (VI \text{ DOY } 97 \dots \text{DOY}305) \quad (2-4)$$

This area under the curve index corresponds to the total growth during the growing season, and may enable the differentiation of C3 from C4 species, because C3 species produce 3-4 times as much biomass as C4 species in northern mixedgrass prairie (Clarke et al. 1943).

Table 2.2: Day of year, start and end of composite period, derivation of VI relative rate of change (DVDT) and number of times touched by smoothing filter data for smoothed within year approach.

		Day of year (DOY)													
		0	1	1	1	1	1	1	2	2	2	2	2	2	3
		9	1	2	4	6	7	9	0	2	4	5	7	8	0
		7	3	9	5	1	7	3	9	5	1	7	3	9	5
Times smoothed		8	9	10	11	11	11	11	11	10	9	8	7	6	
Start of composite		7	23	9	25	10	26	12	28	13	29	14	30	16	1
		Apr	Apr	May	May	Jun	Jun	Jul	Jul	Aug	Aug	Sep	Sep	Oct	Nov
End of composite		22	8	24	9	25	11	27	12	28	13	29	15	31	16
		Apr	May	May	Jun	Jun	Jul	Jul	Aug	Aug	Sep	Sep	Oct	Oct	Nov
Derivation of DVDT		DVDT1		DVDT3		DVDT5		DVDT7		DVDT9		DVDT11		DVDT13	
		DVDT2		DVDT4		DVDT6		DVDT8		DVDT10		DVDT12			

2.3.3 Ancillary Spatial Data

To incorporate ecologically relevant gradients with the aim of improving model performance, two additional data inputs were selected for model inclusion. Percent sand fraction was used as a proxy for soil texture, and was created as a 250 m raster from an existing soils polygon database (McNeil 2003). Soil rasters were created by converting to percent sand fraction, using crosswalk tables developed by the province of Alberta (Agricultural Region of Alberta Soil Inventory Database 2001).

At landscape scales, topography (elevation, slope, and aspect) is a major factor that determines the spatial variability of solar insolation, contributing to microclimates which give rise to different vegetation communities (Fu and Richard 2002). Solar insolation was generated within the ArcMap 10.0 toolbox (Esri 2012), and was used as a coarse-scale proxy for slope, aspect, and topographic position, using a 250 m re-scaled (bi-linear interpolation) 1:250000

digital elevation model (source data = 75 m), downloaded from the Canadian Digital Elevation Database (CDED 2011) via the Geobase portal. As the influence of topography, slope, and aspect on rangeland vegetation are all related to solar insolation (Whitman and Wolters 1967), the solar insolation model was deemed to be the most robust proxy variable; the model was configured to produce an area solar radiation raster representing accumulated watt hours per meter square (WH/m^2) between DOY 97 and DOY 305, latitude = 50° , day interval = 16 days, hour interval = 0.5 h (remainder of settings were set to default).

2.3.4 Field Data Collection and Processing

Field data designed to describe the ratio of cover between C3 and C4 species within a MODIS pixel were collected between the months of July and September, 2010 to 2012. Data collection consisted of the identification of a specific vegetation community using range guides describing 177 communities within CFB Suffield (Smith 2010), 42 communities of the dry mixedgrass subregion (Adams et al. 2005) and 45 communities of the moist mixedgrass subregion (Adams et al. 2004). Community descriptions provide statistical measures of canopy cover and constancy by species. Using GPS coordinates to identify the precise centre of each MODIS pixel, community assessments were made at 5 locations near each corner and centre (Fig 2.3), comprising 23 % of a pixel, by identifying the most-similar plant community to each location. For each of the 5 subsamples, the most-similar vegetation community to the site was recorded for tabulation of cover of C3 and C4 species. The conversion from community information to C3 and C4 species' cover was carried out by summing the canopy cover of species for the corresponding community, and averaging them across the 5 subsamples to represent the overall composition of C3 and C4 species within the MODIS pixel.

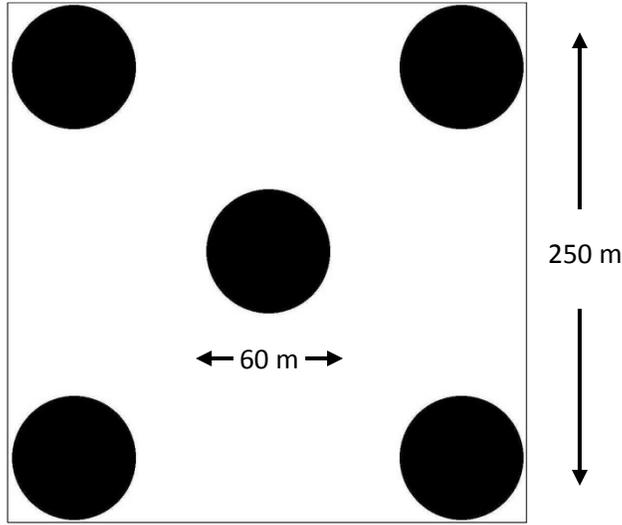


Figure 2.3: Field sampling area of assessment (black circles) within each MODIS pixel.

A total of 286 pixels were assessed in field; of these, 229 were training pixels collected in 2010 and 2011, located by stratified random sampling using mean fire frequency and soil texture as stratifiers. Large wetlands and previously cultivated lands (mapped by Alberta Sustainable Resource Development, 2010) were avoided to reduce undesired variability in species composition. An additional total of 57 sites were collected in 2012 for use as an independent validation. Field data was uploaded into a point shapefile in ArcMap 10.0, for the extraction of MODIS VI data. The extraction of MODIS VI data in relation to field data (C3 and C4 species' cover) enabled the PFT classification, by incorporating both field data and MODIS VI data into a geospatial database for the creation of PFT classes by multiple logistic regression.

2.3.5 PFT Classification by Logistic Regression Models

After the tabulation of C3 and C4 species' canopy cover for each pixel, the data was converted to a ratio of C3 to C4 species, whereby:

$$\text{Functional Ratio (FR)} = (\text{coverC3} - \text{coverC4}) / (\text{coverC3} + \text{coverC4}) \quad (2-5)$$

FR values therefore range in value from -1 to 1. To enable the creation of logistic regression models which predict values between 0 and 1, FR values were then re-scaled such that:

$$\text{Logistic Functional Ratio (LFR)} = (\text{Functional Ratio} + 1) / 2 \quad (2-6)$$

Multinomial logistic regression (MLR) models the probability of a multi-category dependent variable based on a set of predictor variables, using the logit distribution function (Agresti 2002). In this study, MLR was used to predict classes of the ratio of cover between C3 and C4 functional types. The effect of different class widths and total number of classes were explored in preliminary PFT MLR models, however the most effective MLR classes corresponded with PFT classes identified by ordination: C3 dominant, C3/C4, co-dominant, and C4 dominant (3 classes; Fig 2.2, Table 2.3). PFT MLR models also used 5 classes with the aim of decreasing classification errors (errors of omission and commission) between classes, but were ultimately re-scaled back to 3 classes (Table 2.3).

PFT MLR models were developed in SPSS 19 (IBM 2010), after all geospatial data were exported from ArcMap 10.0. PFT MLR models were created using LFR values as the explanatory variable, percent sand fraction, and solar insolation as forced entry predictor variables, and various inputs of VI attributes in forced entry and stepwise fashion as described in Table 2.4. Using VI data, two different phenological time periods (short and long) were explored: 7 rasters (DOY 97 to 193; short) or 14 rasters (DOY 97 to 305; long).

Table 2.3: Plant functional type (PFT) descriptor, ratio of canopy cover (C3:C4), functional ratio (FR) and logistic functional ratio (LFR) bins for PFT logistic regression models.

PFT Descriptor	Ratio of Canopy Cover C3:C4	3 Class Logistic Regression		5 Class Logistic Regression	
		Functional Ratio (FR)	Logistic Function Ratio (LFR)	Functional Ratio (FR)	Logistic Function Ratio (LFR)
C4 dominant	< 1:1.5	-1.0 to -0.2	0 to 0.4	-1.0 to -0.6	0 to 0.2
				-0.6 to -0.2	0.2 to 0.4
C3/C4 co- dominant	$1.5:1 \leq$ $\geq 1:1.5$	-0.2 to 0.2	0.4 to 0.6	-0.2 to 0.2	0.4 to 0.6
C3 dominant	> 1.5:1	0.2 to 1.0	0.6 to 1.0	0.2 to 0.6	0.6 to 0.8
				0.6 to 1.0	0.8 to 1.0

Table 2.4: Logistic regression model combinations, including forced entry variables, vegetation index (VI), smoothing type, and VI attributes by model type.

Forced Entry Variables	x	VI	x	Smoothing Type	x	Model Type	
						Forced Entry	Stepwise
percent sand,		EVI		unsmoothed		DOY97 to DOY193	DOY97 to DOY305
radiation		NDVI		smoothed within year		DVDT1 to DVDT6	DVDT1 to 13
				smoothed across years		DVDT1 to DVDT13	iVI

Using relative rate-of-change (DVDT) data derived from the original VI product, similar time periods were explored: 6 rasters (DVDT1 to DVDT6; short) or 13 rasters (DVDT1 to DVDT13; long).

To further illustrate, after the forced entry of percent sand fraction and solar insolation variables, PFT MLR models could include either NDVI or EVI (unsmoothed, or smoothed across years, or smoothed within year), comprised of either short or long time spans of VIs, or short or long time spans of relative-rate-of-change rasters, in stepwise or forced-entry fashion. Since *i*VI was routinely rejected as a statistically significant predictor variable in forced-entry models during data exploration, it was only used for selection in stepwise models.

2.3.6 PFT Classification Performance Evaluation

PFT MLR models were evaluated for performance using a two-stage process, by initially assessing pseudo- R^2 values and then assessing classification accuracy. The 60 best-performing models with the highest pseudo- R^2 were then assessed for overall accuracy and Cohen's weighted kappa (Cohen 1968), which measures the agreement between predicted and observed features of ordinal data.

To assess classification accuracy, PFT MLR rasters were created by exporting model data from SPSS 19 to ArcMap, and then intersected with independent ground-truth data. Error matrices were generated by comparing predicted PFT states to observed PFT states. Because the aim of this study was to create the most-accurate multi-temporal PFT classification, Cohen's weighted kappa was used as the overall determinant of model performance, as it was deemed most important to minimize the accuracy error between ranked FR classes. For example, disagreement between observed and expected values of non-adjacent classes (e.g., C3 dominant

and C4 dominant) should be penalized more than disagreement of two adjacent classes (e.g., C3 dominant and C3/C4 co-dominant). Because there were insufficient sample sizes to analyze differences in accuracy between ecological units, results were simply pooled.

2.4 RESULTS

As summarized in Table 2.5, the majority of the best-performing PFT MLR models used NDVI (13/15), employed yearly temporal smoothing (9/15), used 3 predictive classes (9/15), and employed forced-entry models (11/15). In the majority of models (12/15), percent sand fraction and solar insolation were both statistically significant predictors. Finally, no model incorporated iVI.

With respect to the incorporation of multi-temporal rasters, only 55 % (6/11) of forced entry models used any VI predictors which provided statistically significant ($p < 0.05$) contributions to model prediction. Further, of the forced-entry models, 45 % (5/11) used raw NDVI values, 27 % (3/11) used shorter-sequence relative rate-of change NDVI values (DVDT1 to DVDT 6), and 27 % (3/11) used longer-sequence relative rate-of change NDVI values (DVDT1 to DVDT13). In contrast, 75 % of the stepwise models used either 2 or 3 statistically significant multi-temporal predictors, and all stepwise models incorporated both raw NDVI and relative rate-of-change NDVI values as predictors.

By plotting VI metrics over time (Fig 2.4), there does appear to be distinct phenological characteristics between each of the three PFT classes for the unsmoothed (UN) NDVI data, particularly between DOY 161 and DOY 241. There are two peaks in NDVI for C4 and C3/C4 co-dominant pixels (DOY 193, DOY225), but only a single peak for C3 dominant pixels (DOY 225).

Table 2.5: Best 15 PFT MLR classification models; smoothing type: SY = smoothed within year; SA = smoothed across years; UN = unsmoothed.

Model ID(VI)	Initial Number of Classes	Smoothing Type	Model Type	Inputs	Pseudo -R ²	Overall Accuracy	Weighted Kappa	Rank
DNSY09BIN53(N)	5	SY	ENTER	DOY97, DOY113, DOY129, DOY145, DOY161, DOY177, DOY193, SAND ¹ , INSOLATION ¹	0.598	0.74	0.5298	1
DNSY09BIN3R(N)	3	SY	ENTER	DOY97, DOY113, DOY129, DOY145, DOY161, DOY177, DOY193, SAND ¹ , INSOLATION ¹	0.464	0.74	0.5198	2
SNSY09BIN3R(N)	3	SY	STEPWISE	DVDT4 ¹ , DOY209 ¹ , DOY273 ¹ , SAND ¹ , INSOLATION ¹	0.455	0.72	0.5150	3
SNSY09BIN53(N)	5	SY	STEPWISE	DVDT4 ¹ , DVDT13 ¹ , DOY225 ¹ , SAND ¹ , INSOLATION ¹	0.565	0.71	0.4665	4
SNUN09BIN3R(N)	3	UN	STEPWISE	DVDT4 ¹ , DOY273 ¹ , SAND ¹ , INSOLATION ¹	0.429	0.75	0.4342	5
VNSY09BIN3R(N)	3	SY	ENTER	DVDT1, DVDT2, DVDT3, DVDT4, DVDT5, DVDT6, SAND ¹ , INSOLATION ¹	0.463	0.68	0.4152	6
NNSY09BIN3R(N)	3	SY	ENTER	DVDT1, DVDT2, DVDT3, DVDT4, DVDT5, DVDT6, DVDT7, DVDT8 ¹ , DVDT9, DVDT10, DVDT11, DVDT12, DVDT13, SAND ¹ , INSOLATION	0.571	0.66	0.3936	7
SNUN09BIN53(N)	5	UN	STEPWISE	DVDT4 ¹ , DVDT5 ¹ , DVDT12 ¹ , DOY97 ¹ , DOY113 ¹ , DOY225 ¹ , DOY273 ¹ , DOY289 ¹ , SAND ¹ , INSOLATION ¹	0.701	0.65	0.3775	8
VNSY09BIN53(N)	5	SY	ENTER	DVDT1, DVDT2, DVDT3, DVDT4, DVDT5, DVDT6, SAND ¹ , INSOLATION ¹	0.575	0.64	0.3719	9
DNUN09BIN53(N)	5	UN	ENTER	DOY97, DOY113, DOY129 ¹ , DOY145 ¹ , DOY161 ¹ , DOY177 ¹ , DOY193, SAND ¹ , INSOLATION ¹	0.535	0.66	0.3210	10
NUN09BIN3R(N)	3	UN	ENTER	DVDT1, DVDT2 ¹ , DVDT3, DVDT4, DVDT5, DVDT6 ¹ , DVDT7 ¹ , DVDT8 ¹ , DVDT9 ¹ , DVDT10 ¹ , DVDT11, DVDT12, DVDT13, SAND ¹ , INSOLATION	0.532	0.63	0.3165	11
DNUN09BIN3R(N)	3	UN	ENTER	DOY97, DOY113, DOY129, DOY145 ¹ , DOY161 ¹ , DOY177 ¹ , DOY193, SAND ¹ , INSOLATION ¹	0.395	0.66	0.3141	12
ESY09BIN3R(E)	3	SY	ENTER	DVDT1, DVDT2, DVDT3, DVDT4, DVDT5, DVDT6, DVDT7, DVDT8, DVDT9, DVDT10, DVDT11, DVDT12, DVDT13, SAND ¹ , INSOLATION	0.557	0.63	0.2936	13
DESY09BIN53(E)	5	SY	ENTER	DOY97, DOY113, DOY129, DOY145, DOY161, DOY177, DOY193, SAND ¹ , INSOLATION ¹	0.519	0.60	0.2936	14
VNUN09BIN3R(N)	3	UN	ENTER	DVDT1, DVDT2, DVDT3, DVDT4 ¹ , DVDT5 ¹ , DVDT6, SAND ¹ , INSOLATION ¹	0.381	0.68	0.2853	15

¹statistically significant explanatory variable (P < .05); (E) = EVI; (N) = NDVI

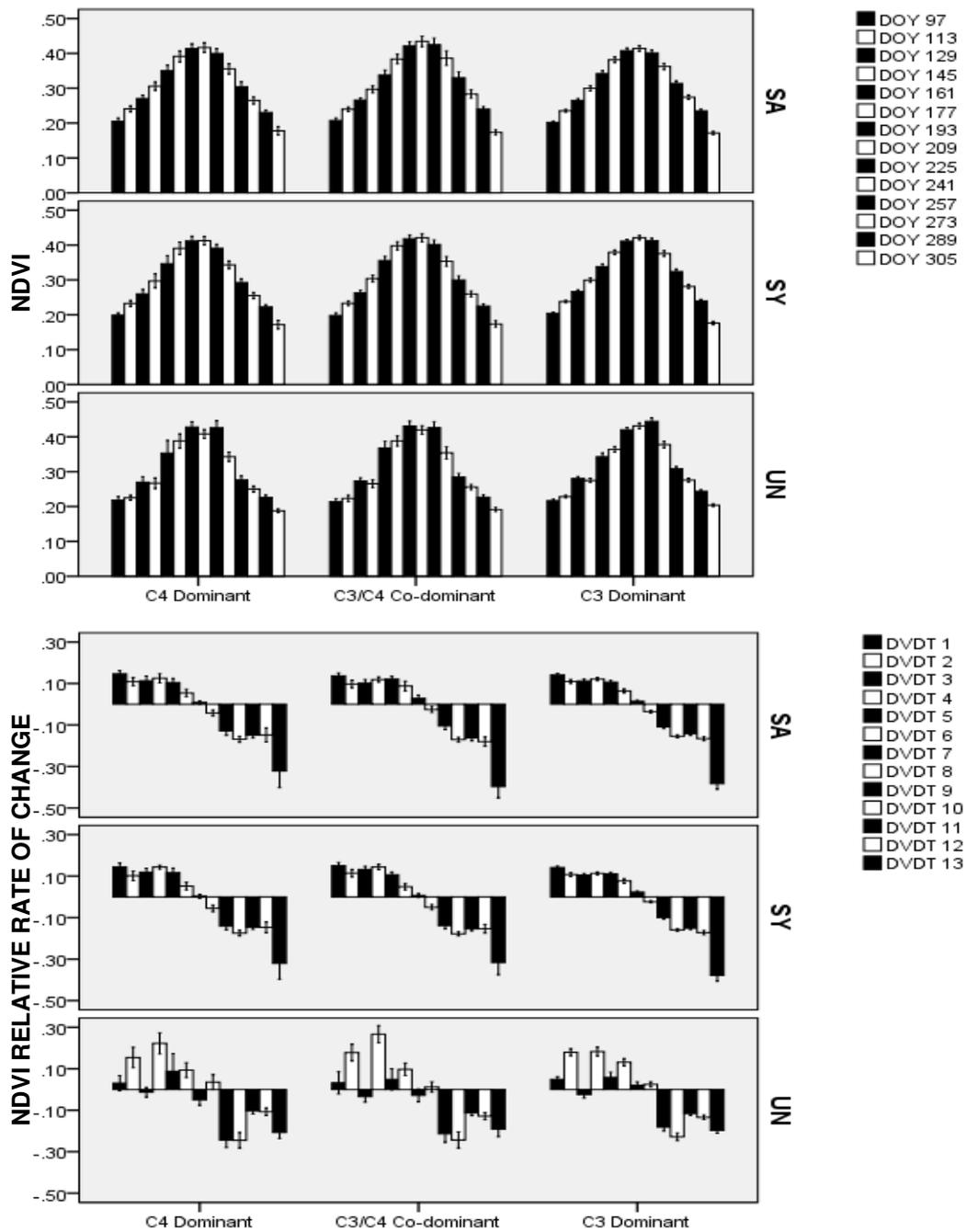


Figure 2.4: Effect of temporal smoothing (smoothed across years/SA; smoothed within year/SY; unsmoothed/UN) on raw NDVI values (above) and NDVI relative rate-of-change values (below). Error bars = 95 % confidence intervals.

However, it appears that the NDVI phenological differences become less visually distinguishable between PFT classes with the use of yearly temporal filtering (SY), and each are virtually with across year (SA) temporal filtering.

The same trends are apparent with unsmoothed (UN) NDVI relative rate-of-change temporal profiles, where rapid increases in photosynthetic activity are seen in DVDT2 and DVDT4 for both C4 and C3/C4 co-dominant pixels, distinguishing them from C3 dominant pixels. Furthermore, the rate of increase of DVDT6 is higher in C3 dominant pixels, distinguishing them from both C4 and C3/C4 co-dominant pixels. Finally, similar to NDVI data, the profiles between PFT classes of NDVI relative rate-of-change data become less visually distinguishable with the addition of within year (SY) temporal filtering, and are virtually indistinguishable with across year (SA) temporal filtering.

With respect to the factors used to assess model performance (Table 2.4), pseudo- R^2 values of the best models ranged from .429 to .701, and kappa values ranged from .2936 to .5298. Finally, there were no statistically significant relationships between pseudo- R^2 values and weighted kappa ($P = .758$).

2.5 DISCUSSION

2.5.1 PFT Classification Performance

As the overall objective of this study was to create an accurate multi-temporal PFT classification, the resulting model explanatory power (pseudo- R^2 ; .60) and overall accuracy (.74) of the best model compare favourably to similar studies employing different sensors and spatial resolutions: Davidson and Csillag (2001; $R^2 = .68$, field radiometer; 10 m effective resolution);

Davidson and Csillag (2003; $R^2 = .69$, overall accuracy = .74, AVHRR; 30 m re-sampled resolution); and Foody and Dash (2007; $R^2 = .60$, overall accuracy = .78, MERIS; 300 m resolution). These results demonstrate that coarse spatial resolution multi-temporal PFT classification using simple phenology metrics compare well to those models employing more-complex phenological characteristics at higher spatial resolutions. It is therefore concluded that the objective has been achieved, and PFT outputs are sufficiently accurate for use in analyzing the spatial relationships between ecosystem states (Fig 2.5) and fire history (Chapter 3). From the spatial distribution of PFTs (Fig 2.5), it is apparent that C4 dominant communities generally occur in the central portions of the base (where the bulk of military training land use occurs), whereas C3 dominant communities generally occur nearer the periphery of the base, where less intensive land use occurs.

In addition to achieving an accurate PFT classification, the results of this work indicate that ecological theory derived from field-based monitoring (Fig 2.2; Smith 2010) can be integrated into remote sensing analysis—an important issue raised by Ustin and Gamon (2010). The ecological framework established by ordination in chapter 1 revealed that PFTs displayed differential responses to land use gradients, and that topographic position and soil texture were important environmental gradients in explaining species composition. We have demonstrated that the incorporation of ecological variables (solar insolation as a proxy for topographic position, and soil texture which were both used as statistically significant explanatory variables in 80 % of best-performing models) improves model performance, by explaining the variance introduced by natural factors.

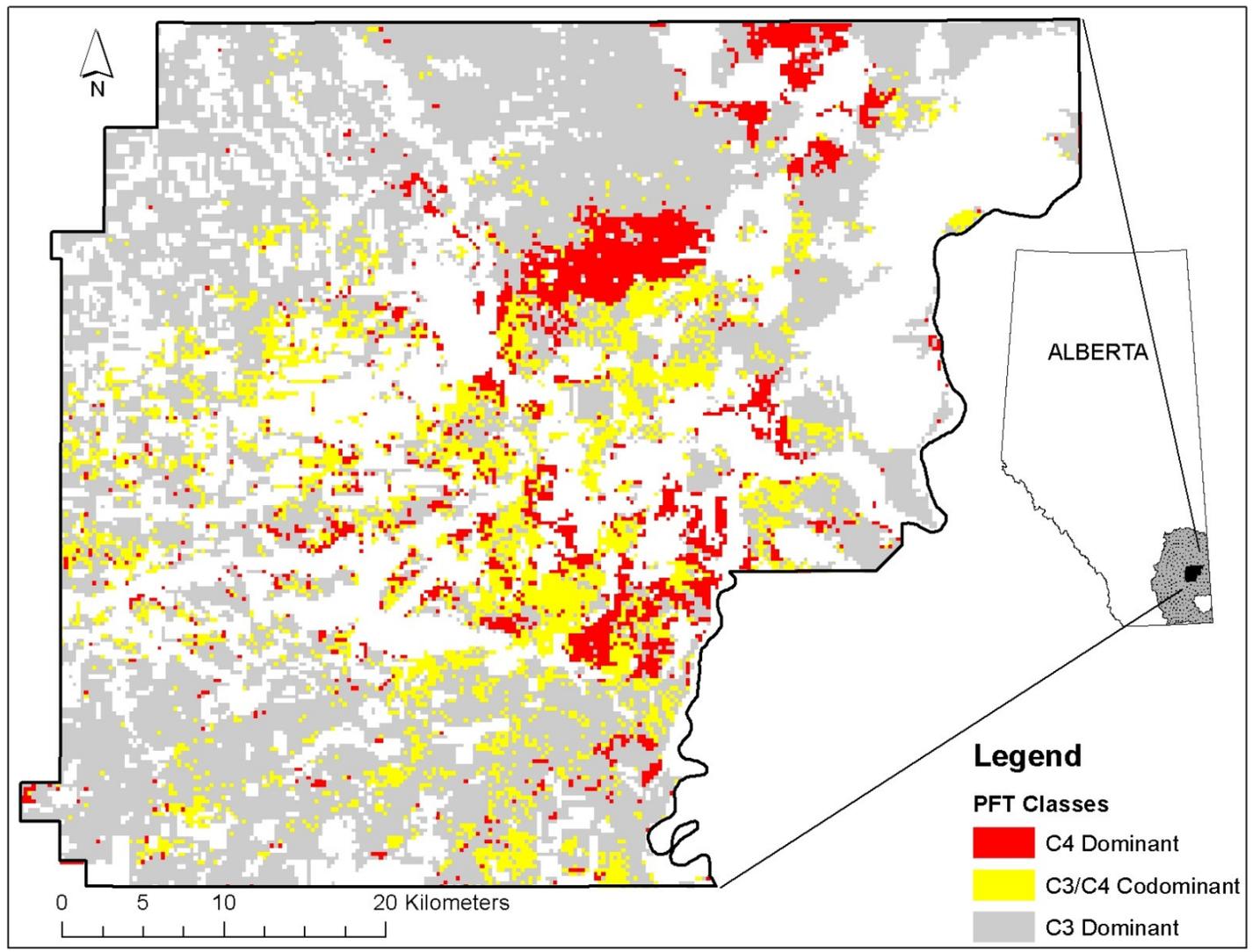


Figure 2.5: Plant functional type (PFT) classification of Blowouts, Loamy, and Sands ecological units (range sites).

While we assessed PFT MLR model performance on classification accuracy by weighted kappa, statistical analysis shows that there were no relationships between weighted kappa and pseudo- R^2 . It is evident from our study that PFT MLR models with higher pseudo- R^2 values did not necessarily result in better classification. We argue that the performance metric used is question-dependent, and note that if our objective was to understand or identify important relationships between remotely sensed data and biophysical processes, parsimony (as measured by information criteria; Reichert and Omlin 1997), or measures of variance described (R^2) would be better indicators of model performance.

With respect to the better performance of NDVI over EVI (only used in 2 of the 15 best PFT MLR models), our results show that despite the extra processing of EVI to compensate for background soil in arid regions (Huete and Liu 1994), this index performed poorly in separating PFTs. While there is limited literature on the utility of EVI in semi-arid regions, previous research has established that EVI is better suited than NDVI for dense vegetation, such as forested areas (Sims et al. 2006). We suggest that further research is required to determine whether EVI is appropriate for use in semi-arid regions, particularly for PFT classification.

Finally, while only 55 % of forced-entry models used any VI predictors which provided statistically significant predictive power to the model, we suggest that contiguous data between the start (approximate DOY 97) and peak of growing season (approximate DOY 225) are required to detect the subtle differences between PFTs in northern dry mixedgrass prairie. This is an important consideration—ecological studies favour the principle of parsimony, where fewer variables which have higher explanatory power (measured by information criteria) are desired to explain complex systems or processes (Reichert and Omlin 1997). While stepwise PFT MLR models may select for the most parsimonious data using information criteria, they may fail to

integrate phenologically important data otherwise captured in forced-entry models. Forced-entry data using pre-defined phenological periods may not provide statistically significant contributions to model explanatory power, but given the erratic nature of blue grama, it is unlikely that stepwise models, other VI metrics, ratios, algorithms or functions can enhance or its C4 phenological profile from C3 species.

2.5.2 PFT Classification Accuracy

There are at least two factors which affected classification accuracy in this study, and which require considerable attention in the design of a PFT study: (i) mixed pixels, and (ii) the treatment of vegetation data as continuous or categorical data. As Foody and Dash (2007) discussed, the sub-pixel level mixing of remotely sensed responses from heterogeneous areas greatly reduces the potential of coarse spatial resolution imagery in multi-temporal image analysis. This scale-dependent problem must be considered in the context of the study questions, but also the spatial extent of the study area. Because this study is aimed at developing PFT maps for analysis of fire ecology (Chapter 3), and because fire is a landscape level disturbance operating at spatial scales larger than MODIS pixels, spatial heterogeneity within a pixel is not considered to be a critical issue. Further, the use of fine scale multi-temporal imagery is impractical because of the large size of the study area, and the computational requirements to support large spatial and temporal datasets.

Another issue which must be considered for the potential to affect classification accuracy is the underlying information classes used in this study, rather than continuous PFT variables. Ordination approaches classify continuous vegetation variables into unique vegetation community classes, based upon assumed resource gradients (McCune and Grace 2002). It is recognized that vegetation types intergrade as a continuum (Schmidtlein and Sassin 2004).

However, Ustin and Gamon (2010) resolve this problem, by arguing that functional types (structural, physiological and/or phenological features to group species in response to environmental conditions or according to their impacts on ecosystems) can be considered as both discrete and continuous. This is because the ecological niches which support specific communities are constrained by resource gradients (Ustin and Gamon 2010); these are the same resource gradients which are sought by ecological ordination methods. We therefore argue that the vegetation classes identified by in support of this research should necessarily describe plant functional types as classes—regardless of the spatial scale of the remote sensing data—because these communities occur in niches defined by regions in multi-dimensional resource space (Hutchinson, 1958), as identified by ecological ordination.

The effect of defined vegetation classes were also discussed by Davidson and Csillag (2003) who noted that error was associated with the choice of threshold values for the membership of the C4 functional classes they defined. However, they still defined class boundaries based on described vegetation types. Regardless, Goodin and Henebry (1997) argued that redefining such class boundaries would simply improve the accuracy of some classes at the expense of others, but with no overall improvement in accuracy. Our results support this argument: 40 % of the best-performing models—including the best model—used a five-class scheme which was ultimately re-scaled to three classes. This was further reinforced by pseudo- R^2 and kappa values of the first- (5 classes, pseudo- $R^2 = .598$, weighted kappa = .5298) and second-(3 classes, pseudo- $R^2 = .464$, weighted kappa = .5198) ranked models, where the only difference between them was the number of classes; the overall accuracy for both models was 74 %. It is likely that PFT MLR models using more classes improved the accuracy between classes (resulting in higher kappa), but more classes did not increase overall accuracy.

2.5.3 Effect of Temporal Smoothing on PFT Classification

Perhaps the most important issue identified in this project is the effect of temporal smoothing on PFT classification accuracies in northern dry mixedgrass prairie. This project used a filter rather than a pre-defined function in order to reduce noise in MODIS data. It appears that some temporal filtering is required to reduce temporal profile noise associated with composite images (smoothed within year; SY), but complete filtering (smoothed across years, SA) alters C4 profiles to such an extent that they can no longer be differentiated from C3 profiles. This is important, because C4 dominant pixels in this study showed bimodal peaks in NDVI, much like the erratic growth profiles of blue grama described by Turner and Klipple (1952) and Benment (1969). This concept is also reflected in model performance, where 60 % of the best-performing models employed yearly smoothing, while the remainder were entirely unsmoothed.

The outcome of temporal smoothing in this study is similar to what was observed by Davidson and Csillag (2003), who suggested that in their temporal trajectory indices derived from smoothed time series data, the ‘true’ shape of C4 species’ seasonal productivity curves may have been suppressed. Given that blue grama is the dominant C4 species at Grasslands National Park (Li and Guo 2012), and its erratic growth profile was further suppressed by smoothing, it is likely that this species confounded their results.

While 67 % of the best PFT MLR models used NDVI relative rate-of-change inputs, we note that its derivation (equation 2-3), can compound error if the pixel value from the first date is erroneously low and/or if the pixel value from the second date is erroneously high. Because of the use of the MODIS image-compositing algorithm to overcome cloud contamination (Huete et al. 1999), error may be introduced within composite images by the algorithm itself. This is because of the limited availability of alternative pixels (typically as low as 5; Huete et al. 2002)

to be selected for gap-filling poor quality pixels when cloud cover contaminates the majority of images within the 16 day compositing period. While this error is reduced by temporal smoothing, it is likely increased by the derivation of the relative rate-of-change, resulting in weaker PFT MLR model performance.

2.5.4 Effect of Weather on Multi-temporal Data

From the results of this study, and others describing the physiology of blue grama, it was likely that its temporal growth profile (reflected in MODIS VI data) was affected by weather. Li and Guo (2012) demonstrated in Grasslands National Park Saskatchewan that the variability of coarse-scale, intra-annual NDVI time series was correlated with both temperature and a time lag of precipitation, with precipitation as the larger determinant of NDVI. Although climate variables (growing degree day, precipitation) were not included as part of the PFT classification models in this project, climate data were downloaded for the nearest available station (Medicine Hat airport) for 2009 (Environment Canada 2011). Correlations were run to determine any relationship between growing degree day and precipitation, and mean NDVI by PFT type, for growth between early season (DOY 97) and peak (DOY 225). Using Spearman's rho for aggregated data (all range sites combined), mean NDVI was correlated with growing degree day ($P < .001$) for all PFT states, but no relationship existed for precipitation (no lag). We suggest that multiple years of climate data (particularly temperature) and VI time series data are required, if they are to be included in future PFT classification models.

2.6 CONCLUSION

This study produced a PFT classification using MODIS-derived VI attributes, ecologically relevant spatial variables, and temporal smoothing, with the goal of developing a standard predictive model to estimate the ratio of canopy cover between PFTs at CFB Suffield Alberta, Canada. Major findings include:

1. The accuracy of PFT classification using coarse spatial resolution MODIS multi-temporal imagery and simple phenological metrics (74% overall accuracy; weighted kappa of 0.53 based on independent test data) compares favourably with the results of similar studies using other sensors and finer spatial resolution data, and provides a reasonable foundation for further studies of the impact of land use and fire regimes across CFB Suffield (Chapter 3);
2. Temporal smoothing significantly modifies the temporal profile of C4 species within this study area, to the point that they may be inseparable from C3 species. All of the best performing models in this study received limited (smoothed within year) or no temporal smoothing. Further, temporal smoothing which applies filters rather than forcing a pre-determined function is more appropriate in northern dry mixedgrass prairie, given the erratic growth of blue grama, the primary C4 species;
3. The best predictive models included ecologically relevant ecological variables (soil texture, radiation), which served to increase model explanatory power; and
4. The use of more information classes in PFT classification may serve to increase the accuracy of specific classes (and increase weighted kappa), but does not increase overall accuracy.

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CHAPTER 3: EXAMINATION OF FIRE-RELATED SUCCESSION WITHIN THE DRY MIXEDGRASS SUBREGION OF ALBERTA USING MODIS AND LANDSAT

3.1 ABSTRACT

Fire is an important landscape-disturbance process historically present across the northern Great Plains. While fire effects are poorly understood in northern mixedgrass prairie, previous research suggests that C4 grasses replace C3 grasses with increasing fire (particularly in the spring). This hypothesis was tested at a landscape scale at Canadian Forces Base Suffield Alberta, by exploring the relationship between ecosystem states inferred from a multi-temporal plant functional type classification, and fire history digitized from the Landsat archive. Probit regression results show that succession processes were different between ecological units, with statistically significant models for C3 and C4 dominant pixels on Loamy range sites ($P < .001$), where C4 dominant pixels completely replaced C3 dominant pixels after 14 fires in 36 years. MODIS MCD45 burned area data indicates that fires occur across the entire growing season with a peak in late summer, when C3 species are typically dormant. While fire timing does not appear to play a role in driving species changes, this ecosystem is generally sensitive to repeated fire, with recovery taking decades.

3.2 INTRODUCTION

Fire is a landscape-level disturbance across the northern Great Plains, serving an important role in cycling nutrients, modifying vegetative structure, and resulting in plant succession (Daubenmire 1968; Wells 1970; Wright and Bailey 1982; Bragg 1995; Anderson 2006). However, fire regimes in the Great Plains have been altered by human activities (Hart and Hart 1997) such that the extent, frequency, and timing of fires are departed from their historical norms (Leach and Givnish 1996).

The effects of fire are different between rangeland communities in North America. In tallgrass prairie (dominated by grasses using the C4 photosynthetic pathway), fire has been shown to increase productivity (Wright and Bailey 1982; Briggs and Knapp 1995) and alter species composition (Abrams and Hulbert 1987; Collins and Gibson 1990). However, in northern mixedgrass prairie (dominated by grasses using the C3 photosynthetic pathway), fire effects are less understood (Redmann et al. 1993; Erichsen-Arychuk et al. 2002). However, in general, fire can reduce productivity (Clarke et al. 1943; Redmann 1978), and the recovery of litter can take many years (Dix 1960) in northern mixedgrass prairie.

Northern mixedgrass prairie is comprised of dry mixedgrass (generally described as needle and thread communities) and mesic mixedgrass (generally described as western porcupine and wheatgrass communities; Coupland, 1950, 1992). Plains rough fescue prairie (*Festuca hallii* [Vasey] Piper) is described as a separate ecotype—occurring as a transitional zone between mesic mixedgrass prairie and boreal forest (Coupland 1961); however, fescue also co-occurs with other species in mesic mixedgrass prairie (Adams et al. 2004).

The effects of fire may vary with community type and fire timing in mesic northern mixedgrass prairie (Redmann et al. 1993; Gross and Romo 2010). For example, Pylypec and

Romo (2003) demonstrated that fire resulted in differential effects to standing crop between fescue grasslands and western porcupine-wheatgrass communities, while Redmann et al. (1993) noted that recovery was slower in western porcupine-wheatgrass communities than fescue grasslands.

Changes in species composition (regressive succession or *retrogression*; Glenn-Lewis and van der Maarel 1992) have been observed as a result of fire in mesic northern mixedgrass prairie, where fire has been shown to reduce fescue (Gerling et al. 1995), and wheatgrass (Coupland 1973). Furthermore, spring fires have been shown to stimulate the production of blue grama (*Bouteloua gracilis* [Willd. Ex Kunth] Lag. Ex Griffiths) and western wheatgrass (*Pascopyrum smithii* [Rybd.] A. Löve) (White and Currie 1983), and increase blue grama biomass as a result of repeated fire (Shay et al. 2001).

While the effect of fire has been the subject of study in mesic northern mixedgrass prairie relatively little is known about its effects in northern dry mixedgrass prairie (Erichsen-Arychuk et al. 2002). Fire effects on soil temperature and moisture are important in semi-arid regions because they affect productivity (Vermiere et al. 2011). Removal of litter increases soil temperatures (Vermiere et al. 2005) and decreases productivity (Willms et al. 1986) because litter reduces evapotranspiration, making more water available for plant growth (Willms et al. 1993).

Similar to fire in mesic mixedgrass prairie, species compositional changes in dry mixedgrass prairie have been observed. Vermiere et al. (2011) showed that western wheatgrass replaced needle and thread grass (*Hesperostipa comata* [Trin. & Rupr.] Barkworth) as a result of fire. Erichsen-Arychuk et al. (2002) found that summer fire and drought reduced productivity, and differentially affected the cover of wheatgrass, depending on topographic position in

southern Alberta. However, Clarke et al. (1943) found that needle and thread-blue grama communities were more tolerant of fire than wheatgrass communities in the same region.

Thus, fire processes resulting in retrogression may be directly related to the selective suppression of a species or functional group based on fire timing (spring fires: Shay et al. 2001; Anderson et al. 1970; White and Currie 1983; Schact and Stubbendieck 1985; Redmann et al. 1993), or indirectly through the modification of structure important for conserving scarce moisture (Dix 1960; Redmann 1978; Willms et al. 1986; Dormaar and Willms 1990; Willms et al. 1993; Dormaar et al. 1994; Vermiere et al. 2005). Critically, Dormaar and Willms (1990), and Dormaar (1994) argued that the grazing-related removal of litter drove previously needle and thread dominant communities to irreversibly regress to blue grama dominant communities.

Restoring fire processes to the landscape has been recommended as a tool to support conservation (Bailey and Anderson 1978; White and Currie 1983; Gross and Romo 2010). However, information is typically unavailable to guide management because fire-history proxies (e.g., charcoal) are a limiting factor in identifying historical regimes in the Great Plains (Scheintaub et al. 2009). Where Wright and Bailey (1982) estimated historical frequencies of the northern Great Plains to be between five and 10 years, analysis of charcoal concentrations in lake sediments in Brush Lake near Sheridan, Montana, indicate that historical frequency ranged from 20 to 40 years, with fire frequencies declining as a result of European settlement (Umbanhowar 1996). In the absence of fire-regime information, experimental research is therefore important in guiding management (Scheintaub et al. 2009). Further, because northern mixedgrass prairie is regularly subject to drought between periods of above average precipitation (Coupland 1958), it is important that rangeland studies span at least part of a wet-dry cycle (Shay et al. 2001).

Rangeland studies are primarily based on the collection of point samples of vegetation and soil attributes at local spatial scales over time. The collected point samples are statistically inferred to larger spatial scales and then compared to reference sites, in order to draw conclusions about status of rangeland condition (Washington-Allen et al. 2006). Such changes are represented by state and transition models, which identify reference and successional ecosystem states (Stringham et al. 2003). However, very few field-based surveys have been conducted at sufficient temporal scales to account for the range of natural variability in measured indicators, detect either succession or threshold change in indicators, or separate human impacts from climatically driven landscape responses (Washington-Allen et al. 2003).

In contrast, ecological indicators derived by remote sensing can provide information at spatial and temporal scales relevant for rangelands management (Tueller 1989; Washington-Allen et al. 2003). Remote-sensing of plant functional types (PFTs) exploits the phenological differences between C3 (cool season) grasses, and C4 (warm season) grasses, with a classification scheme which falls between species-specific and broad vegetation types (Ustin and Gamon 2010). A remote-sensing approach designed to exploit phenological differences between PFTs is relevant in answering ecological questions (Adjorlolo et al. 2012), including land use effects on ecosystem function (Tiezen et al. 1997) and ecosystem changes as a result of environmental change (Davidson and Csillag 2001). C4 species are generally better adapted to conditions of high light (Tieszen 1970), high temperature (Schuster and Monson 1990), and low soil moisture (Barnes et al. 1983) than C3 species.

Because of differences in physiology between C3 and C4 species, and with studies indicating that PFTs have differential responses to fire (Shay et al. 2001; Vermiere et al. 2011), PFT-based remote-sensing has the potential to complement field-based studies of fire ecology,

by providing spatially explicit landscape-level information, which is limited by the logistical requirements of collecting large volumes of data from point sources. For example, Smith and McDermid (*in review*) used a logistic-regression-based classification of multi-temporal Moderate Resolution Imaging Spectroradiometer (MODIS) normalized difference vegetation index (NDVI) 250 m 16-day composites to predict three functional classes (C3 dominant, C3/C4 co-dominant, and C4 dominant) in northern dry mixedgrass prairie, with an overall accuracy of 74% (weighted kappa = 0.53).

The results of this previous work formed the basis of the present investigations into fire-related ecological succession at Canadian Forces Base (CFB) Suffield. The primary objective of this study was to examine the effect of repeated fires across a 36-year (1972 to 2007) time span on plant communities within the northern dry mixedgrass prairie. We achieved this by analyzing the spatial relationships between contemporary (2009) ecosystem states derived from MODIS PFT classification and inter-year fire history observed from the Landsat archive: the longest-available free satellite-remote-sensing archive (Woodcock et al. 2008).

Based on previously established state and transition models, we hypothesized that the spatial extent of C3 dominant communities (primarily needle and thread) would be negatively correlated with the total number of fires, whereas the spatial extent of C4 dominant communities (blue grama) would be positively correlated with the total number of fires, in the process of retrogression. We further hypothesized that the recovery (progressive succession from seral states to climax) of disturbed sites would be correlated with the total number of fires at the site; wherein infrequently burned sites would proceed directly towards the climax community (C3 dominant), and more-frequently burned sites would undergo a succession from C4 dominant

communities to C3/C4 co-dominant communities, and then ultimately to C3 dominant communities.

Finally, because of previous research suggesting that retrogression is driven by either fire timing (where spring fires suppress C3 species) or by the removal of litter (favouring drought tolerant C4 species), MODIS monthly burned area data (Roy et al. 2008) was used to determine whether intra-year fire timing was an important factor in explaining succession. While the complete fire history was digitized by Landsat, the specific timing of fires using this data could not be recorded. However, MODIS monthly burn data has sufficient temporal sensitivity to explicitly assign fire timing. We hypothesized that fire timing was not restricted exclusively to the spring months, and as a result, was not related to long-term succession.

3.3 DATA AND METHODS

3.3.1 Study Area and Ecology

CFB Suffield is situated within the Northern Great Plains of North America, approximately 300 km southeast of Calgary, Alberta, within the dry mixedgrass subregion of the Alberta (Strong and Leggat 1992; Fig 3.1). Vegetation is dominated by native grassland, interspersed with areas of abandoned cultivation where the land was broken prior to the establishment of the Base in 1971. CFB Suffield is the largest Army training facilities in Canada, with a total area of 2690 km². Land use disturbances at CFB Suffield include vegetation and soil compaction resulting from wheeled and tracked military vehicles, frequent fires resulting from various munitions, bare ground resulting from excavation and trenching of military and petroleum infrastructure, and vegetation trampling and removal by cattle grazing. Since the inception of military training (1972), exercises and associated fires generally commence in May and end in October, resulting in areas which burn frequently (Fig 3.1).

Although frequent fires occur in the central areas of the base corresponding with military training, infrequent fires occur across its entirety. As a result, the diversity of fire frequency may permit the statistical analysis of the spatial arrangement of ecosystem states inferred from MODIS, relative to fire history.

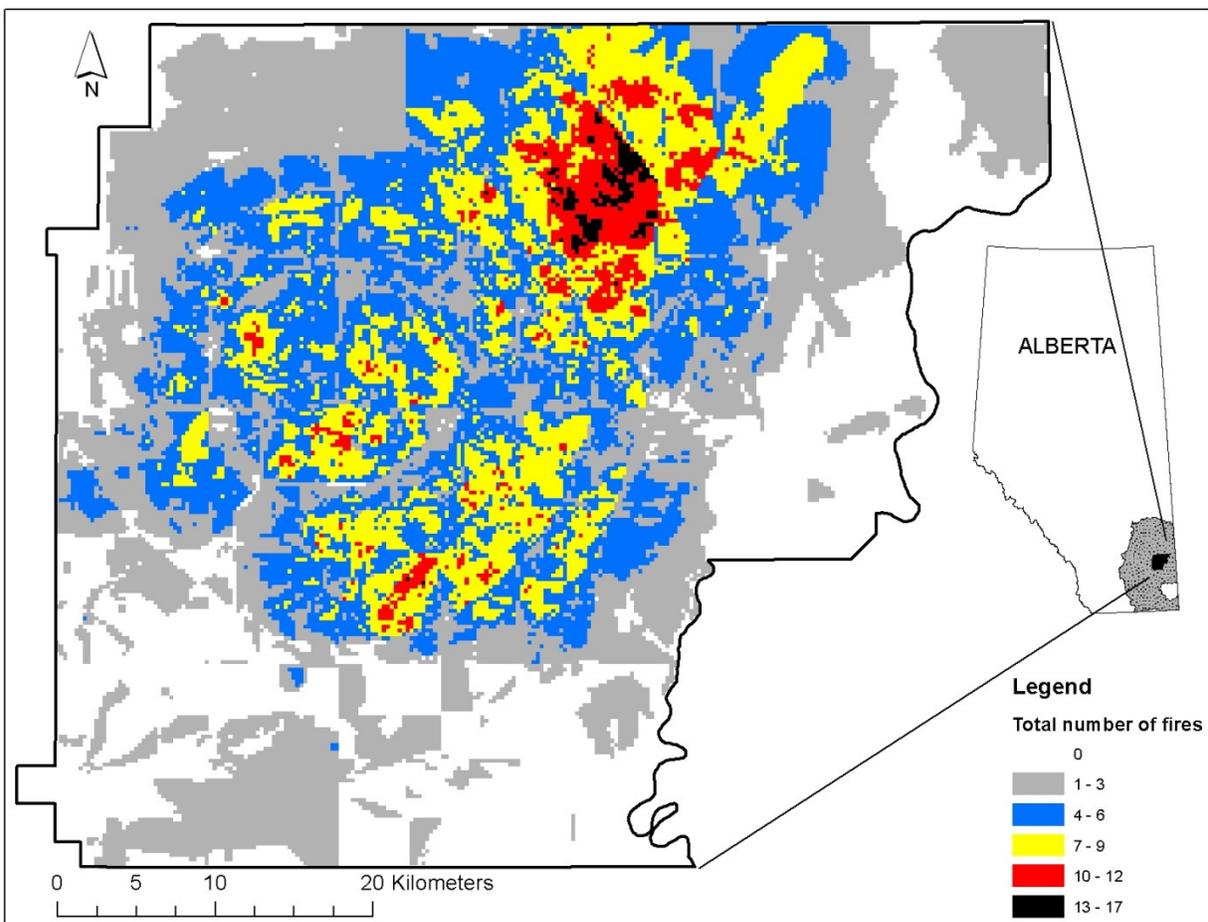


Figure 3.1: Total number of fires (1972 to 2007) within CFB Suffield, as digitized from the Landsat archive (inset: grey stipple = dry mixedgrass subregion of Alberta).

Plant communities within the study area fall within the *Stipa-Bouteloua* faciation described by Coupland (1950). The predominant C3 grasses by canopy cover are needle and thread (ubiquitous), and western wheatgrass and northern wheatgrass (*Agropyron dasystachyum* [Hook.] Scribn.), both of which are consistently present on solonetzic and very coarse-textured soils (Adams et al. 2005; Smith 2010). Of the four C4 species grass present—blue grama, sandreed grass (*Calamovilfa longifolia* [Hook.] Scribn.), plains muhlenbergia (*Muhlenbergia cuspidata* [Trin.] Rydb.), and little bluestem (*Schizachyrium scoparius* [A. Michx.] Nees), only blue grama exists with canopy cover consistently greater than five percent at the landscape scale (Smith 2010). These C4 species are in the northern extent of their range and exist under conditions that are marginal for growth, and so are highly responsive to subtle changes in environmental conditions (Davidson and Csillag 2003). For example, spring growth of blue grama begins only when the 10-day moving average soil temperature of the upper 15 cm exceeds 10.5° C (Detling et al. 1978).

Predominant range sites subject to ongoing land use include Blowouts (5 % of study area; hardpan and solonetzic pits co-occurring with Loamy sites), Loamy (30 %; typically associated with morainal landforms, and includes loam, silt loam, silt, clay loam, sandy clay loam, and silty clay loam soils), and Sands (20 %; typically associated with glaciofluvial or low relief eolian landforms, and includes loamy sand and sand soils; Alberta Sustainable Resource Development 2010). Each range site gives rise to distinct vegetation communities (climax/reference), and land use disturbance results in succession which can generally be described by state and transition models (Bestelmeyer et al. 2003).

By long-term monitoring of vegetation and land use, species compositional changes have been revealed by ordination methods (de-trended correspondence analysis/DCA; McCune and

Grace 2002), where species' responses to fire can be visualized as an ordination plot, which arranges species' cover in multi-dimensional ecological space (Fig 3.2). From this analysis, state and transition models have been developed representing distinct successional states where relatively undisturbed/reference states (C3 dominant communities) undergo retrogression to C3/C4 co-dominant communities, and ultimately to C4 dominant communities, with increasing levels of disturbance, particularly relating to fire (Weerstra 2005, 2010, 2012, Smith 2010; Table 3.1). To investigate the relationship between fire and species composition, spatially-explicit fire maps were required to develop a history of fire since training began.

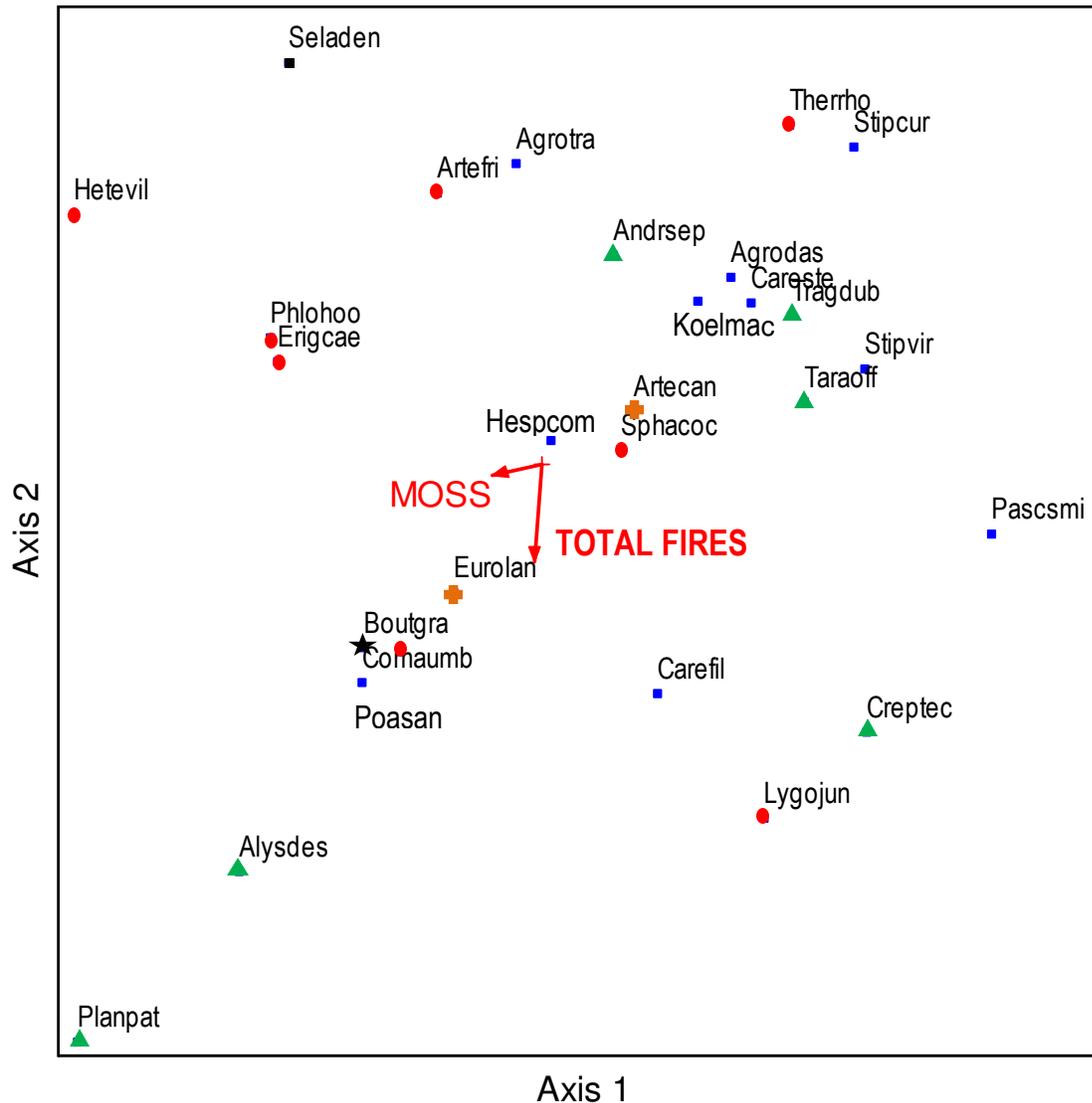


Figure 3.2: Ordination of species in ecological space for Loamy range sites with joint-plot overlays of environmental variables (moss = moss cover, total fires) with $r^2 > .10$. Blue square = C3 grass, black square = cryptogram, green triangle = annual, red circle = forb, brown cross = shrub, black star = C4 grass, Agrodas (*Agropyron dasystachyum*), Agrotra (*Agropyron trachycaulum*), Alydes (*Alyssum desertorum*), Andrsep (*Androsace septentrionalis*), Artecan (*Artemisia cana*), Artefri (*Artemisia frigida*), Boutgra (*Bouteloua gracilis*), Carefil (*Carex filifolia*), Careste (*Carex stenophylla*), Comaumb (*Comandra umbellata*), Creptec (*Crepis tectorum*), Erigcae (*Erigeron caespitosus*), Eurolan (*Eurotia lanata*), Hespcom (*Hesperostipa comata*), Hetevil (*Heterotheca villosa*), Koelmac (*Koeleria macrantha*), Lygojun (*Lygodesmia juncea*), Pascsmi (*Pascopyrum smithii*), Planpat (*Plantago patagonica*), Poasan (*Poa sandbergii*), Phlohoo (*Phlox hoodii*), Seladen (*Selaginella densa*), Sphacoc (*Spharalcea coccinea*), Stipcur (*Stipa curtisetata*), Stipvir (*Stipa viridula*), Taraoff (*Taraxacum officinale*), Therrho (*Thermopsis rhombifolia*), and Tragdub (*Tragopogon dubius*). Ordination derived from 95 long-term monitoring plots.

Table 3.1: Range sites and successional states represented by mean canopy cover.

Range Site	Successional State	Sample Size	Ecosystem State	Mean canopy cover (std dev) by species		
				Blue grama	Needle & thread	Northern wheatgrass
Blowouts	Reference	10	C3	17.4 (8.6)	21.4 (12.3)	6.9 (10.5)
	Successional	5	C3/C4	19.8 (7.4)	14.5 (9.4)	5.3 (3.9)
Loamy	Reference	19	C3	10.6 (13.2)	36.4 (20.2)	8.8 (11.6)
	Successional 1	30	C3/C4	38.4 (14.1)	30.1 (8.2)	1.6 (2.4)
	Successional 2	3	C4	64.8 (5.7)	12.5 (1.9)	0.1 (0.2)
Sands	Reference	17	C3	16.0 (10.7)	52.8 (9.5)	2.5 (4.3)
	Successional	18	C4	40.1 (22.2)	22.9 (8.9)	2.5 (5.6)

3.3.2 Fire Mapping by Landsat Data

Landsat has been used in a variety of research designed to study fire (Chuvieco et al. 2002; Hudak and Brocket 2004; Smith et al. 2007). Such studies employ image transformations designed for Landsat, including the tasseled cap (Rogan and Yool 2001) and normalized burn ratio (NBR; Picotte and Robertson 2011), which is derived as:

$$\text{NBR} = (B4 - B7) / (B4 + B7) \quad (3-1)$$

NBR is useful for both delineating burn scars, and also identifying burn severity (Picotte and Robertson 2011). The results of these studies suggest that Landsat is an appropriate data source for mapping fire extent; however, automated detection is particularly problematic because of the spectral diversity of burned areas, and the time elapsed since fire occurrence (Pereira and Setzer

1993; Chuvieco et al. 2006). As a result, some fire mapping projects rely solely on visual interpretation of Landsat data (Bastarrika et al. 2011).

In total, 61 Landsat images were used to digitize fire history, with the goal of using an early and late season image for each year. Data was downloaded from the EOS gateway (EOS 2006; Table 3.2), geo-rectified, and transformed to the tasseled cap (Kauth and Thomas 1976; Crist and Cicone 1984; Huang et al. 2001) and NBR (Roy et al. 2006) indices, which were used to assist in the manual delineation and digitization of burns scars. Where imagery for an entire year was unavailable, relative-difference images were made between images from the year before and the year after, to identify fires.

Burn scars were delineated by detecting high soil brightness values and/or low NBR values relative to the surrounding area, defined by a clear boundary. While automated classification of burn scars was attempted, resulting outputs contained problematic errors of commission—where other land use impacts (resulting in increased bare ground, also appearing as high soil brightness) were classified as burn scars. As a result, only manual interpretation was used. During digitization, burn polygons were verified against available military firefighting logs, which contain information on the spatial extent and location of fires, but have only been maintained since 2001.

Table 3.2: LandSat data used for digitization of fire history at CFB Suffield.

Year	Early Season Image	Date	Late Season Image	Date
1972	N/A	N/A	LM10430251972294	20-Oct-72
1973	LM10420250073215	03-Aug-73	LM10430250073270	27-Sep-73
1974	LM10430251974193	12-Jul-74	LM10430250074301	28-Oct-74
1975	LM10420250075187	06-Jul-75	LM10430250075224	12-Aug-75
1976	LM20430250076156	04-Jun-76	LM10420250076272	28-Sep-76
1977	LM20430250077204	23-Jul-77	LM20420250077275	02-Oct-77
1978	N/A	N/A	N/A	N/A
1979	N/A	24-Jun-79	LM30430251979275	02-Oct-79
1980	N/A	N/A	LM20420251980278	04-Oct-80
1981	N/A	N/A		12-Sep-81
1982	N/A	N/A	LT403902500823145	10-Nov-82
1983	N/A	N/A	N/A	N/A
1984	LT50390251984104	13-Apr-84	LT50390251984280	06-Oct-84
1985	LT50390250085202	21-Jul-85	LT50400250085273	30-Sep-85
1986	LT50390251986093	03-Apr-86	LT50390251986301	28-Oct-86
1987	LT50390251987096	05-Apr-87	LT50400251987279	06-Oct-87
1988	LT50390251988099	08-Apr-88	LT50400251988266	23-Sep-88
1989	LT50390251989101	11-Apr-89	LT50400251989284	11-Oct-89
1990	LT50390251990136	15-May-90	LT50390251990296	02-Oct-90
1991	N/A	N/A	LT50390251991267	23-Sep-91
1992	LT50390251992158	06-Jun-92	LT50400251992277	03-Oct-92
1993	LT50400251993119	28-Apr-93	LT50400251993295	21-Oct-93
1994	LT50390251994131	10-May-94	LT50400251994298	24-Oct-94
1995	LT50390251995150	26-May-95	LT50400251995269	26-Sep-95
1996	LT50400251996160	08-Jun-96	LT50390251996281	07-Oct-96
1997	LT50400251997130	09-May-97	LT50400251997290	16-Oct-97
1998	LT50400251998117	27-Apr-98	LT50400251998277	03-Oct-98
1999	LT50390251999145	24-May-99	LT50400251999264	20-Sep-99
2000	LT50390252000180	28-Jun-00	L7204002502520001017	17-Oct-00
2001	L7204002502520010427	27-Apr-01	L7104002502520010817	17-Aug-01
2002	L7103902502520020829	29-Aug-02	L503902502520021024	24-Oct-02
2003	L7104002502520030519	19-May-03	L7103902502520031003	03-Oct-03
2004	L7203902502520040717	17-Jul-04	L7204002502520041113	13-Nov-04
2005	L7204002502520050422	22-Apr-05	L504002502520051023	23-Oct-05
2006	L503902502520060715	15-Jul-06	LT5040025000626710	24-Sep-06
2007	LT5040025000712610	06-May-07	L503902502520070803	03-Aug-07

3.3.3 Fire History and Spatial Attribute Database

A GIS database using ArcMap 10.0 (Esri 2012) was constructed for each 250 m MODIS pixel, where its geographic centroid was recorded as an attribute and matched to geo-located environmental and land use information. Associated attributes which were appended to each MODIS pixel included its current ecosystem state (inferred from PFT classification), fire history (1972 to 2007), range site, land use, and topographic position, all extracted by spatial join to the pixel centroid. For each year, presence/absence was used to describe fire history: where a fire intersected the centroid of the pixel, it was recorded as a fire event (1), otherwise absence was recorded (0). Range site data was extracted from a polygon database produced by Alberta Sustainable Resource Development (2010). Range site data describes the relevant soil and topographic attributes which support different vegetation communities. Land use presence/absence information for each pixel was also extracted into the following categories: garrison/built-up, military training, and cattle grazing.

A 1:250,000 digital elevation model (75 m) was downloaded from the Canadian Digital Elevation Database (CDED 2011), re-scaled to a 250 m resolution product (bilinear interpolation), and used to derive topographic position with the topographic position index (TPI) tool for ArcMap (Jenness 2006). Topographic position is a key variable to control in rangeland studies, because different topographic positions have different hydrogeological rates (erosion, hydrology) resistance, resilience, and potential for biotic communities (West 2003). The TPI tool was used to classify the landscape into six distinct topographic positions: valley, lower slope, upper slope, mid slope, upper slope, and ridge.

3.3.4 MODIS MCD45 Burned Area Product

As Landsat data was used only to identify inter-year fire history, MODIS MCD45 burned area product were used to identify precise intra-year fire timing for the years downloaded (2001 to 2009). MCD45 data is provided as a monthly 500 m raster containing per-pixel burning and quality information, including the approximate Julian day of burning within a 16 day window (Roy et al. 2008). The MODIS burned area algorithm (Roy et al. 2005) detects rapid changes in vegetation growth, by assessing daily surface reflectance time series in a bidirectional reflectance model to deal with angular variations found in satellite data, and the use of a statistical measure to detect change probability from a previously observed state. After detecting statistically significant changes in vegetation, the algorithm assigns an approximate day of burning for each pixel.

MODIS MCD45 data were downloaded from the Land Processes Distributed Active Archive Center (LP-DAAC 2005), re-projected to NAD83 UTM Zone 12, and converted to vector using ArcMap 10.0. Vector data was then summarized as total area burned by month and total area burned by year. In order to assess the accuracy of the burned area product relative to manual digitization, the detection rate (DR) of MCD45 data was derived as:

$$DR_{(MCD45)} = (\text{total annual burned area}_{(MCD45)}) / (\text{total annual burned area}_{(Landsat)}) * 100 \quad (3-2)$$

3.3.5 Pixel Selection for Limiting Variance Prior to Statistical Analysis

It is critical that rangeland studies control for unwanted variability (West 2003) and also account for human causes of change (Washington-Allen et al. 2003) in order to preserve the signal of the relevant ecological processes of interest. In order to limit variation in the fire history and spatial attribute database prior to statistical tests, pixels were removed when their PFT class could be affected by land use other than fire, or their presence was affected by topographic variance. For example, blue grama is naturally dominant on dry hillcrests (Smith 2010); the inclusion of such C4 dominant pixels could interfere with the establishment of statistical models which seek to explain their presence solely in relation to fire history.

The following were removed prior to further analysis: pixels which had burned between 2008 and 2009 (to remove any effect of fire-induced misclassification of PFTs); pixels located in cattle grazing pastures (where grazing-induced succession could be falsely associated with fire); pixels of garrison/built-up land use, where cultivation has occurred and introduced C3 species are deliberately grown; pixels with ridge (naturally dry and sparse, favoring arid C4 species) and valley positions (naturally moist, favoring mesic C3 species; Smith 2010), derived from the TPI tool; and pixels of C3/C4 co-dominant and C4 dominant states, where no fires had occurred (i.e.: succession associated with a different disturbance process). While the removal of pixels effectively reduced sample sizes for analysis, it was important to remove as many factors as possible which contribute to undesired noise attributed to environmental variability and land use. After pixel selection, Blowouts (1393 pixels), Loamy (4713 pixels), and Sands (3432 pixels) range sites, which did not contain previous cultivation, were then analyzed separately.

3.3.6 Statistical Analysis

Fire-Related Retrogression

All statistical analyses were conducted using SPSS 19 (IBM 2010). Where most ecological studies favour the use of logistic regression to model the dependence of categorical data on proportional data ranging from 0 to 1 (Trexler and Travis 1993), probit regression is appropriate for response-based sampling, where sampling is not random but is instead stratified by the discrete variable of an outcome (Manski 1981). Probit regression was used to test for significant relationships between the proportions of each ecosystem state and the total number of fires experienced (response-based).

Post-Fire Resilience and Progressive Succession

Because it is logistically difficult to investigate ecological change over long time spans, spatial sequences are often used as direct substitutes for temporal sequences in a concept known as ergodicity (Gregory et al. 2009). If the ergodic hypothesis in ecology (Molchanov 1992) is valid, then the climax state of a succession system represents a spatially developed time history of succession, and the areas making up a plant community should be proportional in a climax state of association to the times of their development in the succession series (Karev 1997). We suggest that the ergodic hypothesis is a useful framework in examining the process of recovery (resilience), by enabling comparisons of the proportions of ecosystem states under different disturbance regimes, where the disturbance history is well established and the time period is fixed.

In order to examine the process of post-fire resilience and progressive succession, the fire history and spatial attribute database was further parsed into two treatments:

1. Burning treatment, where pixels were subject to 18 years of no burning (1972 to 1989), followed by 18 years of burning (1990 to 2007); and
2. Recovery treatment, where pixels were subject to 18 years of burning (1972 to 1989), followed by 18 years of rest (1990 to 2007).

Chi-square tests were run to compare the pixel counts of each ecosystem state by the number of times burned for each range site, in order to determine the direction of change and identify significant differences in proportions suggesting recovery (e.g., increased proportion of C3 dominant pixels correlating with rest). We hypothesized that there would be significant differences in the proportions of C3 and C4 dominant pixels between treatments: where the number of C3 dominant pixels would be significantly higher in the recovery treatment than the burning treatment; and the number of C4 dominant pixels would be significantly lower in the recovery treatment than the burning treatment. The Blowouts range site did not have sufficient sample sizes to run statistical tests.

Fire Timing

Fire timing was analyzed by comparing MODIS burn extent between spring (May-June) and summer (July-September) fires, using the non-parametric equivalent of the paired t-test—the Wilcoxon signed rank test—as only 9 years of burn data was used.

3.4 RESULTS

3.4.1 *Fire-Related Retrogression*

Probit regression models were statistically significant ($P < .001$) for C3 dominant pixels on Loamy and Blowouts range sites (Table 3.3), where the number of C3 dominant pixels was negatively related to the total number of fires. The regression model for C4 dominant pixels on Loamy range sites was significant ($P < .001$), where the number of C4 dominant pixels was positively related to the total number of fires; however, C4 dominant pixels on Blowouts range sites were statistically unrelated to fire history ($P = .403$).

In contrast to Loamy and Blowouts range sites, there was no statistically significant relationship ($P = .881$) between the number of C3 dominant pixels and the total number of fires on Sands range sites (Table 3.3). As visualized in Figure 3.3, succession processes are different between range sites, with the proportion of C3 dominant pixels decreasing in relation to the total number of fires for Blowouts and Loamy range sites, but not for Sands. In contrast, C3/C4 co-dominant pixels on Loamy and Sands range sites appear to rise to a peak (approximately 4-8 fires in 36 years; Fig 3.3) and then decrease in relation to the total number of fires.

Table 3.3: Probit regression results with total number of fires (m) as predictor of ecosystem state.

Range Site	Ecosystem state	$m \cdot x + b$	Std Error	Z Statistic	Sig	95 % CI (lower, upper)	
Blowouts	C3	-.436 + 1.488	.120	-3.634	.000	-.671	-.201
	C3/C4	.234 -1.886	.033	7.145	.000	.170	.299
	C4	.096 -2.542	.114	.836	.403	-.129	.320
Loamy	C3	-.301 + 1.312	.028	-10.823	.000	-.356	-.247
	C3/C4	.081 - 1.377	.008	9.514	.000	.064	.097
	C4	.224 - 2.045	.014	15.681	.000	.196	.252
Sands	C3	-6.700 + 5.238	44.812	-.150	.881	-94.53	81.13
	C3/C4	.366 - 2.922	.124	2.964	.003	.124	.609
	C4	.614 - 1.938	.057	10.751	.000	.502	.726

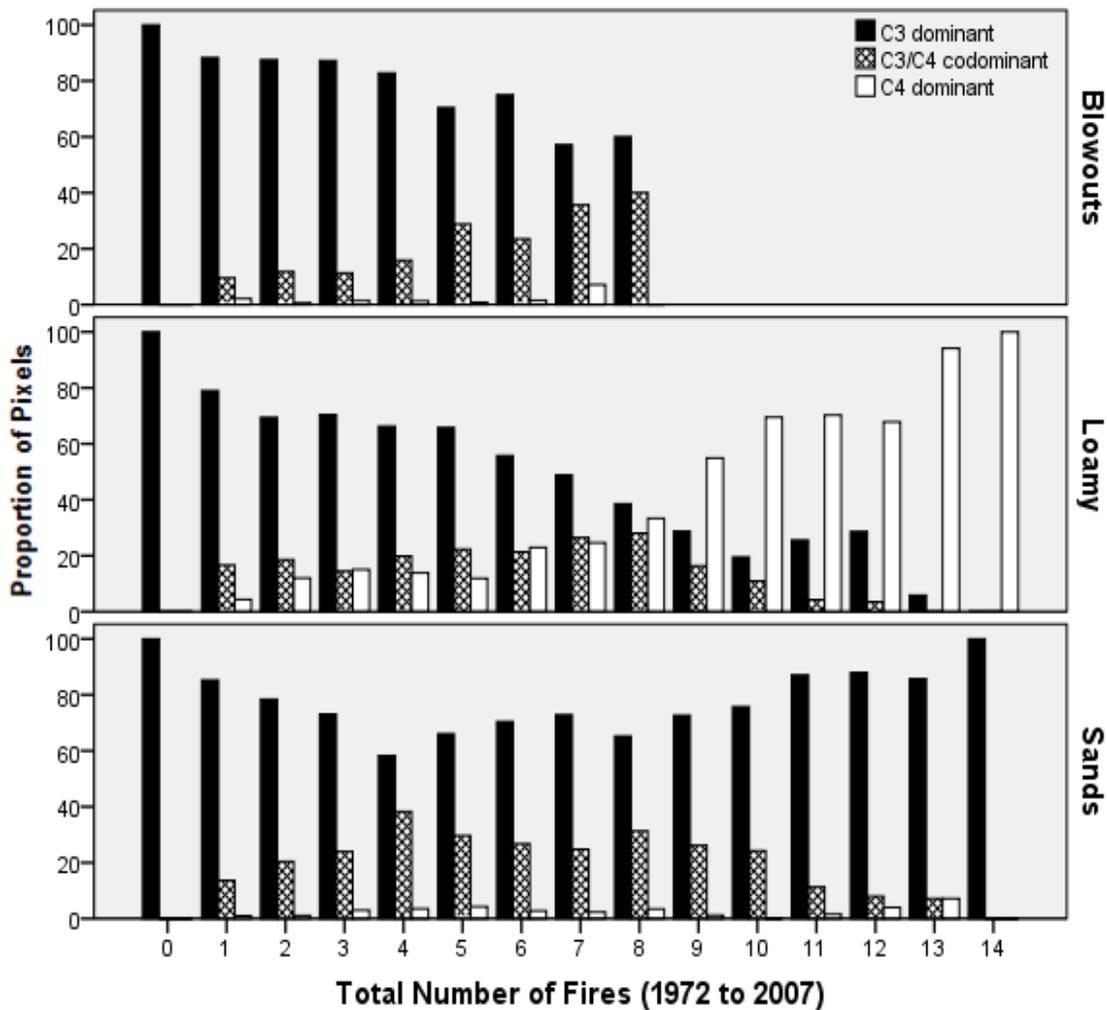


Figure 3.3: Proportion of ecosystem states by number of fires for Blowouts, Loamy, and Sands range sites.

3.4.2 Post-Fire Resilience and Progressive Succession

In all burning treatments with at least one fire in Loamy range sites, the number of C4 dominant and C3/C4 co-dominant pixels was significantly higher, and the number of C3 dominant pixels was significantly lower ($P < .05$) than the recovery treatment (Table 3.4). After 3-6 fires on Loamy sites, C4 dominant pixels comprise the majority of ecosystem states of the burning treatment (88 %). However, after the same number of fires in the recovery treatment—but with at least 18 years of rest—C3 dominant pixels are significantly higher than C4 dominant pixels ($P < .05$) and comprise the majority of ecosystem states (69 %; Table 3.4).

In contrast to Loamy range sites where C4 dominant pixels ranged from 8 to 88 % in the burning treatments, only 1 to 5 % of pixels exist as C4 dominant in the Sands burning treatments. However, with 18 years of rest following 3-6 fires in the Sands recovery treatment, there was a similar proportion of C3 dominant pixels (65 %) to the Loamy recovery treatment (69 %; Table 3.4).

Table 3.4: Number of pixels of ecosystem states (C4 dominant: C4, C3/C4 co-dominant: C3/C4, C3 dominant: C3) by treatment (burning/recovery), and number of fires.

Range Site	Number of fires	Number of pixels of ecosystem states by number of burns								
		Not burned 1972-1989, burned 1990-2007 (E); burning treatment			Burned 1972-1989, not burned 1990-2007 (O); recovery treatment			Difference in proportions (O-E)		
		C4	C3/C4	C3	C4	C3/C4	C3	C4	C3/C4	C3
Loamy	0	0	0	1281	0	0	1281	NA	NA	NA
	1	15	25	152	18	101	446	-5% ¹	5% ¹	0%
	2	10	14	31	20	46	190	-10% ¹	-8% ¹	18% ¹
	3-6	15	1	1	14	12	59	-72% ¹	8% ¹	64% ¹
Sands	0	0	0	765	0	0	765	NA	NA	NA
	1	3	51	149	6	70	607	0%	-15% ¹	15% ¹
	2	1	28	79	2	33	134	0%	-6% ¹	6% ¹
	3-6	2	11	30	2	5	13	5%	0%	-5%

¹Significant difference ($P < .05$)

3.4.3 Fire Timing

Based on MODIS MCD45 data, the majority (spatial extent) of detected fires occur in August (mean = 36 %; range = 0 to 97 %) and September (mean = 21 %; range = 0 to 88 %; Table 3.5). Results of the Wilcoxon signed rank test showed statistically significant differences between the spatial extent of spring (May-June) and summer fires (July-September), with the majority of fire occurring in the summer ($P < .05$). However, it must be noted that the mean detection rate of MCD45 burned area product is 37 % (range = 19 to 80 %), when compared to manually-delineated burn scars from Landsat.

Table 3.5: Percent of total annual burned area (2001-2009) for summer months at CFB Suffield, derived from MODIS MCD45 burned area product compared to Landsat digitized burns.

Year	Percent of total annual burned area						Total annual burned area (ha)		MODIS detection rate (DR)
	May	Jun	Jul	Aug	Sep	May to Sep	MODIS MCD45	Landsat	
2001	0	0	0	97	0	97	4950	25888	19.1%
2002	0	0	0	0	0	0	0	0	NA
2003	0	0	1	10	88	99	19025	42906	44.3%
2004	2	0	44	0	34	80	1250	2588	48.3%
2005	17	0	0	0	0	17	1650	5056	32.6%
2006	0	2	15	54	29	100	28575	35681	80.1%
2007	5	0	1	79	10	95	4550	15469	29.4%
2008	9	0	2	82	3	95	4350	21613	20.1%
2009	47	0	0	0	23	70	22300	40100	55.6%
Mean	9	0	7	36	21	72	9628	21033	36.6%

3.5 DISCUSSION

3.5.1 Fire-Related Retrogression

While Blowouts pixels experienced fewer total fires than other ecological units, this range site appears more resistant to fire-related retrogression than Loamy, where C4 dominant pixels do not generally increase with total fires, but where C3/C4 co-dominant pixels increase at the expense of C3 dominant pixels. Because Blowouts range sites are less productive and are inherently moisture limiting in the dry mixedgrass prairie (Willms et al. 2002; Adams et al. 2005), we suggest that fires are likely to be less frequent because of the slower re-growth of litter. Furthermore, we suggest that shallow rooted species like blue grama have no competitive advantage on this range site type because solonchic soils place greater physical and chemical limitations on plants than other range sites, significantly impeding root growth (Willms et al. 2002).

In contrast to Blowouts, repeated fire in Loamy range sites resulted in the complete transition from C3 dominant pixels to C4 dominant pixels after 14 fires in 36 years. These results are similar to the succession observed by Shay et al. (2001), where frequent burning at CFB Shilo was associated with an increase in blue grama cover. This C4 species is very drought tolerant and is able to make efficient use of small precipitation events (Sala 1985), and can increase recruitment following drought (Fair et al. 1999). We suggest that on Loamy range sites, the long-term effects of fire are similar to grazing-related succession—by the persistent removal of litter—resulting in elevated soil temperatures and increased evapotranspiration, which favour C4 species, which are more tolerant of warmer and drier conditions. For example, Smoliak et al. (1972) showed that after 19 years of continuous heavy grazing on *Stipa-Bouteloua* prairie, shallow-rooted species like blue grama replaced deeper rooted species on the drier

environment induced by heavy grazing. Hart (2001) observed similar trends on the shortgrass steppe, where heavy grazing resulted in the increased cover of blue grama and a corresponding decrease of needle and thread.

In contrast to Loamy range sites (where C3 dominant pixels were removed after 14 fires in 36 years), C4 dominant pixels were completely removed after 14 fires in 36 years on Sands range sites. Because blue grama is a shallow rooted species, we suggest that fire-related effects (litter reduction, increased evapotranspiration) favour deep rooted species which are able reach moisture deeper into coarse textured soils, where soil moisture is severely limiting at the surface. Hugenholtz et al. (2010) suggest that wheatgrasses are able to develop deep root systems to cope with surface moisture limitations in eolian landscapes. Furthermore, Coupland and Johnson (1965) showed that the rooting depth of blue grama averaged 19 cm less than needle and thread and 29 cm less than western wheatgrass. Such physiological differences in grass species explain the stark differences in successional processes between range sites. As a result, the hypothesis regarding the fire-related retrogression of grass species from C3 to C4 species is accepted for Loamy range sites, with the understanding that biophysical differences between range sites result in different successional processes.

In mixedgrass prairie, moisture is the most limiting factor for plant growth (Coupland 1958; Sala et al. 1988), and frequent litter removal impairs production on dry mixed prairie (Willms et al. 1986). Surface litter reduces evapotranspiration (Willms et al. 1993), but also reduces surface temperatures (Redmann 1978). Conversely, removal of litter increases surface soil temperatures (Vermiere et al. 2005), and drier soils on burned prairie have been attributed to increased evapotranspiration (Bremer and Ham 1999), and to reduced water capture (Debano 2000). Finally, the rate of litter accumulation is almost the same as the rate of decomposition

(Coupland 1973), and litter build-up after fire takes many years (Dix 1960). Given these considerations, it is highly likely that the physical removal of litter by fire is the primary driver for succession, by increasing evapotranspiration and increasing soil temperatures. These physical changes to the soil surface result in different effects to PFTs, based on soil texture and chemistry: where litter removal favours drought-tolerant C4 species on Loamy range sites, favours deeper rooted C3 species on Sands range sites, but confers only limited advantage to C4 species on Blowouts range sites.

3.5.2 Post-Fire Resilience and Progressive Succession

With respect to post-fire resilience, our results support the hypothesis that ecological progression from seral states (C4 dominant) to reference (C3 dominant) on Loamy range sites is dependent on the number of fires, where the proportion of C3 dominant pixels declines with the total number of fires, even with significant rest. That only 69 % of pixels were C3 dominant after 3-6 fires followed by 18 years of rest suggests that the complete re-establishment of climax C3 species after repeated fire in dry mixedgrass prairie may take decades. Critically, Dormaar and Willms (1990) showed that the removal of grazing pressure in overgrazed *Stipa-Bouteloua* communities did not necessarily result in succession back to the climax species. Further, Dormaar et al. (1994) argued blue grama is resistant to displacement by associated climax species, either by allelopathy (Dormaar and Willms 1990), or by competing more effectively in the drier environment (Weaver and Albertson 1956; Kemp and Williams III 1980). Dormaar et al. (1994) also showed that while blue grama dominated sites did show an increase in climax species like needle & thread (correlating with an increase in litter after grazing pressure was removed), the dominance of blue grama was only released by cultivation, where moisture was

higher than under heavy grazing, and where needle & thread was able to rapidly re-established its dominance.

Similar to Loamy range sites, recovery of C3 dominant pixels after repeated (3-6) fires on Sands range sites appears to take decades, with only 65 % of samples comprised of C3 dominant pixels after 18 years of rest. However, this low value may simply be due to the small number of pixels (20) in the recovery treatment. Regardless, successional processes are different on Sands range sites relative to Loamy range sites, and do not fully support the hypothesis that recovery is affected by repeated fire: where the number C4 dominant pixels increase in relation to total fires on Loamy range sites, Sands range sites appear highly resistant to fire-induced selection of C4 dominant pixels. As previously discussed, it appears that with repeated fire, shallow rooted C4 species (blue grama) have no competitive advantage over C3 species on coarse textured soil.

3.5.3 Fire Timing

Where previous studies have shown that spring fires favour C4 species at the expense of C3 species (Shay et al. 2001; Anderson et al. 1970; White and Currie 1983; Schact and Stubbendieck 1985; Redmann et al. 1993), MCD45 burn area data indicates the majority of fires at CFB Suffield tend to occur in late summer, when C3 species are dormant. This supports the hypothesis that fire timing is not directly related to successional processes in dry mixedgrass prairie. However, even with the low mean rate of detection by MODIS (37 %), MCD45 data reveals that fire is not limited to any particular part of the growing season, and as such does not selectively favour C4 species by spring burning. Rather, the persistent removal of litter (and resulting increase in soil evapotranspiration) is a more probable cause for inducing succession.

3.5.4 Application of Methodology to Tame Pasture Range Sites

Although the original study objectives were to assess fire ecology in three range sites dominated by native vegetation, we used the previously described methods on Tame Pasture range sites, to demonstrate the utility of this analysis. Tame Pasture is identified as areas of grasses, legumes or mixtures, planted for grazing or forage production (Alberta Sustainable Resource Development 2010). Previous research at CFB Suffield (McInnes et al., in review) mapped tame pasture fields in order to delineate native prairie from non-native species.

The predominant tame pasture species at CFB Suffield is crested wheatgrass (*Agropyron cristatum* sensu amplo (L.) Gaertn.; a C3 species), which is problematic because of its invasive nature (Harris and Wilson 1970; Box 1986), and its ability to displace native species (Henderson and Naeth 2005). While crested wheatgrass can be controlled with herbicide (Hulet et al. 2010), repeated fire may be an alternative method of control.

Results of this analysis show that C3 tame pasture species showed a statistically significant decline ($P < .001$) in response to fire, where 100 % of PFT pixels are C3 dominant with no fire, and decrease to 25 % with 11 fires in 36 years (Fig 3.4). Similarly, C4 dominant pixels showed a statistically significant relationship with fire ($P < .001$), comprising 5 % of PFT pixels with no fire, and increasing to 50 % of PFT pixels with 11 fires. Based on previously described state and transition models (Smith 2010), it is inferred that blue grama has replaced crested wheatgrass as the dominant species. Again, the results of this demonstrate that ecological theory describing succession (Table 3.1; Smith 2010) can be explored through remote sensing and GIS-based analysis.

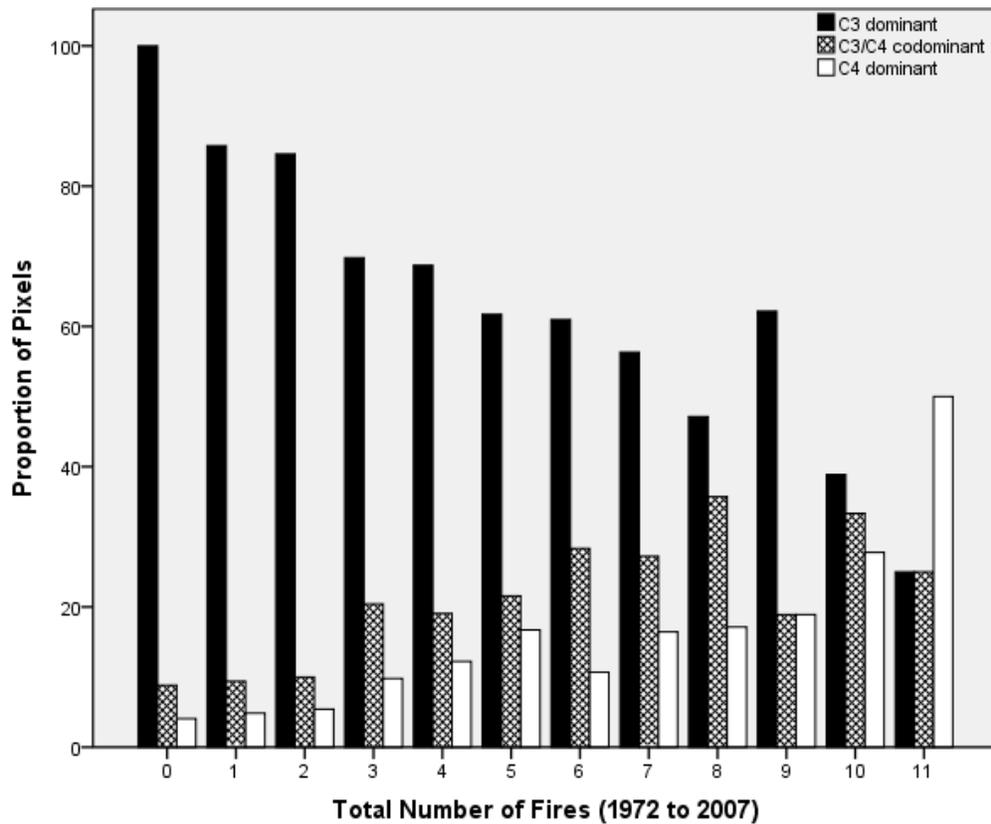


Figure 3.4: Proportion of ecosystem states by number of fires for Tame Pasture range sites.

3.6 MANAGEMENT IMPLICATIONS

In the absence of specific management objectives, we suggest that the maintenance of at least 50 % of the landscape as C3 dominant communities is a useful starting point for fire management goals at CFB Suffield, as a diversity of successional communities is favoured to support endemic species (Adams et al. 2005). With this objective, we recommend that fire frequency does not exceed once every 5 years (7 fires/36 years) for Loamy range sites, and 4 years (9 fires/36 years) for Blowouts. However, where Loamy and Blowouts experience declines in the proportion of C3 dominant communities with increasing fire, Sands range sites appear resistant to transitions to C4 dominant communities, even with very high fire frequency.

However, because of the potential for C4 dominant communities to reach an alternative (and irreversible) steady-state (Dormaar and Willms 1990; Dormaar 1994), management and monitoring must focus on whether such sites can revert back to reference conditions in the long-term.

With respect to grazing management, many studies have established that cattle preferentially graze more grass on burned sites than unburned (Barker and Erickson 1971; Willms et al. 1980; Willms et al. 1981; Erichsen-Arychuk et al. 2002) because of their rapid green-up. However, grazing inhibits the short-term recovery of climax species and impedes the accumulation of litter (Erichsen-Arychuk et al. 2002). Given that the proportion of C3 dominant pixels declined to under 80 % with just one fire and 18 years rest, we support the conclusion by Clarke et al. (1943) that dry mixed prairie needs many years of rest to recover, and echo the recommendations of Erichsen-Arychuk et al. (2002) that grazing management should be adjusted after fire, in order to facilitate recovery with a particular focus on the re-accumulation of litter. As the goal of grazing management is to maximize the sustained productivity of pastures (Adams et al. 2005), it is also critical to note that C3 species produce 3-4 times more above-ground biomass than C4 species in northern mixedgrass prairie (Clarke et al. 1943). Repeated fire therefore has the effect of significantly reducing productivity by the replacement of C3 species with C4 species, which also must be considered in managing both fire and grazing on the same landscape, which is the case at CFB Suffield.

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CHAPTER 4: SUMMARY AND CONCLUSIONS

4.1 RESEARCH CONTRIBUTIONS

This research project has achieved the two main objectives identified: (i) developing an accurate PFT map (pseudo- $R^2 = .598$, weighted kappa = .53, overall accuracy = .74); and (ii) exploring fire-related succession using the PFT map in relation to fire history, where probit regression models established statistically significant relationships between PFT classes and fire history. This research also provides new insights for assessing ecosystem function by multi-temporal remote sensing, and novel methods for studying the fire ecology of rangelands. Firstly, with respect to the creation of a ground-truthed PFT map, the results of this research show that temporal filtering is an appropriate smoothing technique in northern dry mixedgrass prairie, because of the physiological responses of the primary C4 species in the region—blue grama—which does not have a predictable phenological profile, rendering function-fitting smoothing approaches impracticable.

Secondly, the novel use of multi-temporal PFT classification now permits a landscape-level assessment of ecosystem function (health) of grasslands within the CFB Suffield, by reliably inferring the spatial distribution of *observed* PFTs (representing distinct ecosystem states), relative to their *expected* state by incorporating ecological data (topography, range site) and theory (ecological site descriptions of reference states, and PFT states defined by ordination). PFT logistic regression models successfully incorporated ecologically relevant spatial datasets which provided significant explanatory power in predicting plant functional types.

Thirdly, PFT information derived from MODIS complemented field-based studies, by providing complete landscape-level information, thereby enabling a robust analysis of the relationship between ecosystem states and their corresponding fire history. To conduct such an analysis using only field-based observations would require a large and complex point-based sampling strategy, which is not a cost-effective or logistically-feasible approach to exploring fire ecology. In contrast, PFT classification enabled the exploration of fire ecology in a range site that was never part of the original objectives, by applying the same methodology contained herein, and without any additional field sampling.

Fourthly, where fire management in the northern mixed prairie has lacked robust long-term research to define management objectives through historical trends, this project—using only remote sensing and GIS-based analysis— has provided spatially and temporally explicit information on fire succession processes within dry mixedgrass prairie, across landscapes and across several decades. Most importantly, this information could not be deduced from existing long-term monitoring data, given that twenty years of land use had already occurred before the establishment of a long-term monitoring program. Furthermore, this research revealed that successional processes related to fire were different between range sites because of their biophysical limitations. Where C4 dominant pixels entirely replaced C3 dominant pixels on Loamy range sites, there were different outcomes on other range sites including the complete resistance of succession to C4 pixels on Sands range sites.

Fifthly, using MODIS-derived statistics of inter-year fire timing, we were able to deduce the likely cause of fire-induced vegetation succession, by ruling out fire timing as a probable cause. Given that fires occur across the growing season at CFB Suffield, and particularly when C3 species are dormant, it is more likely that the persistent removal of litter by fire causes soil

quality changes (increased temperature, increased evapotranspiration), which favours drought-tolerant C4 species like blue grama on Loamy range sites but due to biophysical limitations of Blowouts and Sands range sites, are more resistant to succession.

Finally, we were able to demonstrate the utility of the methods designed for this study by applying them to a separate range site. We were able to show that C3 dominant pixels in Tame Pasture range sites also transition to C4 dominant pixels with increasing fire, which suggests that fire may be an effective landscape-level management tool to control the invasion of tame species like crested wheatgrass in northern dry mixedgrass prairie.

4.2 SUGGESTIONS FOR FUTURE WORK

While this work has contributed to the understanding of the spatial and temporal patterns fire ecology in northern dry mixed prairie, some applications of this work can be extended into future research, particularly in the use of PFT classification to examine fire ecology in other ecological units at CFB Suffield (in Choppy Sandhills landscapes for example). Further, because PFT classifications provide temporally-explicit vegetation information, they are likely to detect ecosystem changes in relation to cattle grazing, where stocking rate information may be used to assess the effect on grass functional types. We recommend that PFT classification be explored as a cost-effective method of assessing cattle grazing effects on range health.

Secondly, because PFT classifications provide temporally and spatially explicit information about plant communities, such information may permit the parameterization of ecological models. The power of ecological models rests in their ability to run user-defined scenarios, which can be used to predict future landscape condition, or to test hypotheses about landscape change (Dale and Winkle 1998), particularly when model results do not fit past data or

when a well calibrated model gives unexpected results (Doak et al. 2008). We recommend the exploration of PFT classifications to parameterize ecological models, in order to form hypotheses about future landscape change in relation to land use and climate change.

The latest complete report from the Intergovernmental Panel on Climate Change (IPCC 2007) suggests that global average surface temperatures may increase by up to 6° C by 2100, with northern latitudes experiencing the most severe changes. The conclusions of the report suggest that the resilience of many ecosystems is likely to be exceeded in the 21st century, by a combination of climate change-related effects including flooding, drought, wildfire, and insects, compounded by human land use changes.

Mitchell and Csillag (2001) modelled the sensitivity of C3 and C4 species' productivity within dry mixedgrass prairie in relation to grazing management and climate factors, including CO₂ concentration, grazing, temperature, and precipitation; their results indicate that precipitation and its variability best explained changes in productivity and that with expected temperature increases and no corresponding increase in precipitation, C3 species' productivity will decline, while C4 species' productivity will not change substantially until the late 21st century, when moisture stress became high enough to induce productivity declines. In related work, by comparing analogous ecosystems in relation to evapotranspiration gradients, Wolfe and Thorpe (2005) suggest that C4 species are likely to increase in eolian landscapes in northern mixedgrass prairie, with increasing predicted temperature increases.

Given the predicted changes in plant functional types in northern dry mixedgrass prairie as a result of climate change, PFT remote sensing has the capacity to reveal how C3 and C4 species respond. Because of the significant differences in productivity between C3 and C4

species in this ecoregion (Clarke et al. 1943), PFT classification can also be used to infer landscape-level productivity changes within rangelands, in order to inform grazing management.

In summary, the outcomes of this research have established appropriate techniques for conducting PFT classifications in northern dry mixedgrass prairie, via temporal filtering and incorporation of ecologically relevant spatial data. Furthermore, this research has established that PFT classification combined with spatially explicit fire history can provide ecological insights into fire ecology that are logistically impossible with field-based sampling. Finally, this research has established ecologically relevant fire management objectives, which are required for CFB Suffield to maintain its regulatory compliance, particularly for Species at Risk.

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