SPATIAL DRIVERS OF SOIL HEALTH IN A POST-FIRE WATERSHED

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ABSTRACT

Spatial Drivers of Soil Health in a Post-Fire Watershed

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Wildland fires are increasing in both severity and intensity leading to severe and lasting biogeochemical effects on soil. The CZU lightning complex started on August 16th, 2020, and burned 86,509 acres causing severe social and ecological damage. To better understand the impact of fire on soil properties at the landscape scale, we created a digital soil mapping model with the inclusion of remotely sensed burn severity covariates. We combined a raster-stack of environmental covariates with rasters for fire severity and soil samples, to disentangle the relative contribution of fire to the spatial distribution of soil properties in the recently burned Little Creek watershed in Santa Cruz, Ca. Soils were sampled via a conditional Latin hypercube sampling design and analyzed for soil health and soil Fe/Al-oxide mineralogy. To ascertain the relative contribution of remotely sensed fire severity covariates and standard digital soil mapping covariates (e.g. SCORPAN factors) to explain the variance in post-fire soil properties, we deployed multi-linear regression and random forest modeling. We report that remotely sensed indicators of fire severity explained the variance of N_{total}, C_{ex}, pH, oxalate extractable P, NO_3^-, and NH_4^+ in both the MLR and RF models at the watershed scale. The inclusion of rasters of fire effects improved the description of target soil property variance, in concert with more traditional raster-based proxies for the soil forming factors, indicating that fire helps explain the spatial variability of these soil properties in recently burned post-fire landscapes. Furthermore, we report that an increase in remotely sensed fire severity led to an increase in sorbed P (as measured via oxalate extractable P), suggesting a potentially
unreported change to post-fire soil P dynamics. Results inform remotely sensed assessment of fire induced changes to soil properties at the landscape scale.

Keywords: Fire-affected soils, thermally altered soils, digital soil mapping, remote sensing, dNBR, RdNBR, BAI, NBRT
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Chapter 1
INTRODUCTION

Forest lands cover 823 million acres of the United States and are vital areas for recreation, timber production, cultural heritage, wildlife habitat, water supply, climate change mitigation and various other ecosystem services (Oswalt et al., 2019; Hoover and Riddle, 2021). However, these critical ecosystems have become increasingly susceptible to the risk of catastrophic wildfire. This is attributed to increased fuel loading from poor forest management and increased fire suppression, as well as climate warming, which has led to extensive drought and extreme weather (Hanson and Odion, 2014; Westerling, 2016; Liu et al., 2021). Globally wildfires have been occurring at an increasing rate, size, and severity (Flannigan et al., 2009). In California alone, 15 of the 20 largest fires have occurred since 2000 (California Department of Fish and Wildlife, 2020). The damages and projected losses due to the 2018 California wildfire season cost an estimated $148.5 billion with the majority of financial losses being indirect (Wang et al., 2021). Therefore, understanding the impacts of wildfire will help to reduce and predict the economic, social and environmental burden of these catastrophic events.

Soil health is the evolving paradigm of soil quality that links soil functions and ecosystem services to soils as a dynamic living system (Fine et al., 2017). Fire may dramatically alter soil health through impacts to the physical, chemical and biological components of soil, but these impacts depend on the degree of thermal damage (Certini, 2003; Alcañiz et al., 2018a; Agbeshie et al., 2022). Thermal damage to soils post-fire can range from negligible to extreme depending upon burn severity and fire residence time (Ngole-Jeme, 2019). With high thermal damage, soil structure fails, nutrients are
volatilized, and microbes are reduced leading to negative effects on soil health, which in turn, causes reduced environmental regeneration post-fire (Certini, 2003; Agbeshie et al., 2022). Soil C is thought to decrease post-fire due to volatilization; however current literature indicates that low intensity fire increases soil C while high intensity fire decreases in soil C (Alcañiz et al., 2018a; Adkins et al., 2019; Pellegrini et al., 2021). Similarly, there is disagreement in the literature regarding fire’s effects to soil nutrients, particularly at varying burn intensities and spatial scales. Impacts to total N range from no change post-fire (Adkins et al., 2019) to an immediate increase, with a resulting decrease after 8 months (Kennard and Gholz, 2001) to a significant increase in soil N for a year post-fire (Alcañiz et al., 2018a). Divalent cations respond similarly dependent on burn severity. For example, Thomaz (2017) reported no change in divalent cations with varying burn intensity, while Kennard and Gholz (2001) indicate a significant increase in divalent cations following low intensity fire. Variations in results may be due to differences in burn intensity and environmental and pedological differences between soil types.

Post-fire soil thermal damage is often quantified and reported as soil burn severity (SBS). SBS is reported in four categories, unburned, low, moderate and high (Parsons et al., 2010). It is measured through field validating remotely sensed vegetation burn severity metrics such as delta normalized burn ratio (dNBR) (Parsons et al., 2010). While SBS provides an important quantification of soil thermal impacts, it does not provide details into the effects of the thermal damage to individual soil properties, but more of a generalized effect to the soil (Lentile et al., 2006; Robichaud et al., 2007). Most of the research into fire’s effects on soil has been done at the plot scale (Pellegrini et al., 2017;
Agbeshie et al., 2022; Jiang et al., 2022), focusing on post-fire erosion and runoff potential, with few reports of watershed scale fire effects to a range of soil properties (Mallinis et al., 2009; Wang et al., 2020). This suggests a significant knowledge gap around post-fire soil health at the landscape scale. Connecting remote sensing at the landscape or watershed scale to fire effects to soils at the point scale may allow us to better understand the landscape scale effect of fire to soil, and facilitate upscaling of fire’s impact and effect on soil health. To the best of the author’s knowledge no studies have reported utilized remotely sensed vegetation burn severity, such as dNBR, to describe variance of post-fire soil health at the watershed scale. Filling this knowledge gap would allow more nuanced post-fire responses from land managers assisting with soil rehabilitation and forest regeneration.

Digital soil mapping (DSM) is widely used technique that combines soil point data with remotely sensed soil proxies for the forming factors (e.g. Normalized Differenced Vegetation Index, slope, etc.), and statistical modeling to predict and map soil characteristics (Zhang et al., 2017). Various examples of DSM to map and model soil health attributes, such as soil cations, pH, soil C and soil N exist in the literature (McBratney et al., 2003; Sanchez et al., 2009; Ma et al., 2019). Results have varied in significance and explained variance in DSM-style models depending on factors such as sample size, soil property, covariates used and much more. However, many studies have been able to achieve models with a minimum $R^2$ of 0.3 (da Matta Campbell et al., 2019) and other studies achieving results with explained variance above 0.7 (Fathololoumi et al., 2020). For example, two of the most predicted soil characteristics are soil organic carbon (SOC) and total nitrogen, which often utilizes remotely sensed covariates such as
NDVI, elevation and slope (Lamichhane et al., 2019a; van der Westhuizen et al., 2023). Soil cations are also commonly mapped utilizing environmental covariates such as Normalized Differenced vegetation Index (NDVI), Enhanced Vegetation Index (EVI), elevation, and flow accumulation in DSM style models (Naimi et al., 2021). DSM-style models (environmental correlation analyses) have also been used to predict amorphous Fe and Al in soil with the use of elevation, precipitation and slope as environmental covariates (Møller et al., 2023). While digital soil mapping has typically been used in a predictive framework to create soil maps and predict soil properties, it can also be used to increase the knowledge of soil pedogenesis (Ma et al., 2019).

Given that remotely sensed data can be used to infer SBS, and DSM can be utilized to describe variance in soil properties at the landscape scale, combining models that describe fire and soil variability may improve our understanding of fire’s effects to soils at the watershed scale. DSM can be leveraged in an inference framework, to understand the relative contribution of fire to the variance of soil properties at the watershed scale. Here, we leverage remotely sensed indicators of fire severity and classic SCORPAN factors to ascertain if including indicators of fire severity into SCORPAN models significantly improves our understanding of fire-induced changes to soil health at the watershed scale. This study aims to disentangle the relationship between remotely sensed burn severity metrics and a suite of soil properties for the understanding of the relationship between remotely sensed indicators of fire severity and critical soil properties. We hypothesize that remotely sensed burn severity metrics (i.e. Differenced Normalized Burn Ratio (dNBR), Burned Area Index (BAI), Normalized Burn Ratio Thermal (NBRT), Relativized differenced normalized burn ratio thermal (RdNBR)) will
significantly describe the variance of soil properties. Furthermore, we posit that fire variables will be variables of importance in SCORPAN models when combined with additional environmental covariates attributable to the soil forming factors. Finally, we suggest that soil properties can be mapped in post-fire landscapes through the combination of SCORPAN environmental covariates and remotely sensed indicators of fire severity, and that these DSM models will explain more than 50% of the variance of soil properties in post-fire landscapes.
Chapter 2
LITERATURE REVIEW

2.1 Wildland Fire:

The historic fire return interval in the Santa Cruz mountains is a debated topic with results ranging 12 years to 40 years, as evidenced by burn scars on Coast Redwood (sequoia sempervirens) (Stephens and Fry, 2005; Jones and Russell, 2015). These fires were due to indigenous people’s fire practices (Keeley, 2002). However, removal of indigenous people and practices, as well as fire suppression, has severely reduced the amount of fire within the Santa Cruz mountains leading to increased fuel loading (Cowman and Russell, 2021). Increased fuel loading creates hotter, more intense fires due to the increased biomass and necromass being incinerated (Hawkins, 2004; Cowman and Russell, 2021).

Wildland fire is controlled by weather, fuels and topography. Fire often moves at a higher rate on steeper slopes and has a higher intensity when in denser vegetation due to increased fuel loading leading to increased vegetation burn severity (Weise and Biging, 1996). In sparse fuel types, fire often moves at a slower rate and has a lower vegetation burn severity due to the lack of fuel adding to the overall intensity of the fire. Fire intensity is defined as how much heat or energy is released from combustion (Parsons et al., 2010; Ngole-Jeme, 2019). Fire controls vegetation density and type, such that the same vegetation type does not always return post-fire, and invasive species may dominate secondary succession (Forrestel et al., 2011). Fire severity, fire intensity vegetation type, biomass accumulation, biome and return interval all have effects on ecosystem response to fire (Xu et al., 2022a). Fire severity is referred to as the total ecological damage a fire
does to an ecosystem while fire intensity is the energy output of a fire (Keeley, 2009a; California Department of Fish and Wildlife, 2020).

General fire severity typically refers to vegetation and is different from SBS. Vegetation burn severity is the total effect of the fire on the vegetative ecosystem, vegetation mortality and vegetation scorch (Lentile et al., 2006; Parsons et al., 2010). Meanwhile, SBS is the quantification of thermal damage to soils only. The SBS attempts to capture the fire induced changes to physical and chemical properties and the effect of fire to surface soil characteristics (Parsons et al., 2010). Many different metrics have been used to create both remotely sensed and field vegetative burn severity classifications. For field indicators, the composite burn index (CBI) and GeoCBI (a modified version of CBI) are the typical field measurements of vegetation burn severity metrics (De Santis and Chuvieco, 2009) while normalized burn ratio (NBR), differenced normalized burn ratio (dNBR), and normalized difference vegetation index (NDVI) are used for remotely sensed vegetation burn severity (Malone et al., 2011; Morgan et al., 2014).

2.2 Soil Burn Severity:

Potential disconnects can exist between vegetation burn severity and SBS. For example, a fire can move through an area quickly causing large amounts of above ground vegetation damage while leaving the soil with only a moderate burn severity due to the lack of residence time despite the high intensity (García-Llamas et al., 2019b; Fernández-Guisuraga et al., 2023b). Conversely, a fire can burn slowly through duff layers at a low to moderate intensity leaving much of the aboveground vegetation unburned and have a high severity soil burn due to an increased residence time (Ngole-Jeme, 2019). Parsons et al. (2010) describes four SBS categories: unburned, low, moderate and high. Low SBS is
when surface organic layers are not completely consumed, still recognizable and most roots are intact to lightly scorched. Moderate SBS is up to 80% of prefire ground cover may be consumed with scorching on roots. High SBS is most pre-fire surface organic matter is consumed and roots are heavily charred or consumed. (Parsons et al., 2010).

2.3 Fire Impacts to Soil Physical Properties:

In addition to the effects on vegetation soil can also be affected by fire through convective, conductive, and radiative heat transfer (Smits et al., 2016). As fire burns along the soil surface, it will combust much of the O horizon. Once the fires heat reaches the A horizon a heat pulse is transferred down the soil column through pore space, organic materials (such as roots) and conduction through mineral soil (Smits et al., 2016; Xu et al., 2022a). However, mineral soil is a poor conductor of heat, leading to fewer heat induced physiochemical changes in soil as depth along the profile is increased (Xu et al., 2022a). The depth of the heat pulse correlates to the depth of biogeochemical changes to the soil (Stoof et al., 2013).

Wildfire affects many physical soil characteristics such as texture, structure, bulk density, color, moisture content, hydrophobicity, and aggregate stability (Maksimova and Abakumov, 2015). However, different soil textures and degrees of thermal damage lead to varying changes in nutrient cycling and responses making it difficult to predict fire affects to soil on a broad scale (Xu et al., 2022a). There is a notable variation in reports of effects of fire to bulk density, with reports of decreased bulk density, no change in bulk density and increased bulk density (Alcañiz et al., 2018b). For example, Kennard and Gholz (2001) report that bulk density increases post high intensity fire after a 6–12-month period. Conversely, Mastrolonardo et al. (2015) report that bulk density decreases
post-fire, potentially due to the breakdown of organo-mineral aggregates (Certini, 2003). The discrepancy between these studies may be due to the time in between the fire and when the samples were collected and the occurrence of a rainy season, allowing for increased settling and movement of ash and other material into void spaces. However, Kucuk and Kahveci, (2020) found the effect of time on bulk density to be insignificant in post-fire soils. Therefore, clear trends in fire’s impacts to bulk density are not evident.

Similar to many other soil properties, aggregate stability has no change or a small increase with low intensity fire, while a decrease has been reported with high intensity fire (Mataix-Solera et al., 2011). Aggregate stability can increase after low and moderate intensity burns due to hydrophobic substances coating soil aggregates with a waxy film. Aggregates that are left post high intensity fire often have increased stability due to cementing oxides created in the pyrogenic process (Certini, 2003). However, aggregate stability typically decreases after high intensity fires due to the organic cements holding soil aggregates together being destroyed and increased erosion from lack of vegetation cover (Certini, 2003; Woods et al., 2007). Erosion increases post-fire due to increased runoff, hydrophobicity and raindrop splash caused by reduction in vegetation which often reduces aggregates (Scott’ and van Wyk, 1990; Woods et al., 2007).

Fire can induce hydrophobicity in soils, but hydrophobicity type and amount depend on factors such as the organic material being combusted, soil texture and intensity of fire (Woods et al., 2007). At temperatures greater than 280 °C hydrophobic compounds are irreversibly broken down. They become gaseous and move down the soil profile and coat singular soil grains and become solid as the temperature decreases. This leaves a waxy coating on the soil particles leading to hydrophobicity (Debano, 1999;
Certini, 2003). Hydrophobicity in low to moderate severity burns, last for relatively short times and is often gone after the first significant wetting rain. In areas of high fire severity, hydrophobicity has been found to last for up to 6 years and hydrophobic particles have been found to be translocated within the soil profile (Debano, 1999).

2.4 Thermal Impacts to Soil Chemical Properties:

A decrease in total soil C and SOC is found post high intensity fire due to the combustion of soil C (Certini, 2003; Alexis et al., 2007; Alcañiz et al., 2018b; Adkins et al., 2019). Post-fire soil C concentrations depend on a host of factors such as climate, texture, burn intensity, soil moisture, vegetation type and soil type (Alcañiz et al., 2016). Volatile organic compounds are lost between 100-300 °C and near total loss of organics is found when soil temperatures get above 450 °C (Kennard and Gholz, 2001; Certini, 2003). Thomaz (2017), found that SOM decreased linearly with an increase in soil temperature during burning periods. Conversely, increases in SOC have also been reported following low and moderate intensity fires. This is most likely due to unburned surface organics and pyrogenic carbon being incorporated into the soil post-fire (Kennard and Gholz, 2001). Pyrogenic C, (a byproduct of natural wildfire) and biochar (an anthropogenic product), are created under anoxic burning conditions (Bird et al., 2015; Maestrini et al., 2015). A significant increase in SOM was found in areas that burnt over 10 years earlier due to the rapid regrowth of secondary succession regimes (Certini, 2003). However, frequent fires have less of an effect on soil C than one large fire, Click or tap here to enter text.reportedly due the accumulation of biomass and more intense burning periods (Xu et al., 2022a).
Low and high intensity fire have varying effects on soil C. Low intensity prescribed fires may increase mineral C storage, indicating that low intensity and prescribed fires may increase the long-term C storage through the creation of pyrogenic carbon (Alcañiz et al., 2016, 2018b; Pellegrini et al., 2021). In contrast, Maslov et al. (2020) found that high intensity fire destroys mineralizable carbon, labile C and microbial C almost completely in both organic and mineral horizons. They also report that mineralizable C increases for 3 years post-fire and then stabilizes at its maximum. Conversely, mineralizable soil C did not vary with fire in a post-fire area within the Sierra Nevada of California (Adkins et al., 2019). This indicates that mineralizable C varies with fire intensity, with a general negative correlation between mineralizable C and fire severity.

Fire can affect N in varying ways depending on severity or duration since fire. Total N has been found to decrease post-fire due to its low temperature of volatilization (200 °C) (Kennard and Gholz, 2001). Meanwhile, in low intensity fires, Alcañiz et al. (2016) found an immediate increase in N post-fire, and no significant decrease in N after a year. It was also reported that N is not affected 2-3 cm under the mineral soil due to a non-significant temperature increase (temperature remains below 100 °C) with low intensity fires (Alexis et al., 2007). Forests soils can become N deficient post-fire and may take between 100-130 years to recover the N lost during some high intensity fires (Nave et al., 2011; Adkins et al., 2019).

In the first 6 months post-fire Ammonium (NH$_4^+$) has been found to decrease but can begin to increase after 6 months. This increase was speculated to be due to a range of changing soil factors such as pH, soil moisture, soil microbes and soil temperature.
Soil nitrate concentrations post-fire have a positive linear correlation with soil organic matter content indicating that the amount of soil organic matter volatilized is a factor in nitrate (NO$_3^-$) concentrations (Kucuk and Kahveci, 2020). Smithwick et al. (2005) reported that NH$_4^+$ tends to have an increase post-fire for up to two years, and then an apparent decrease after the two-year mark. They also found that nitrate concentrations tend to lag behind NH$_4^+$ concentrations and may be similar to pre-fire conditions for up to a year post-fire. NH$_4^+$ and Nitrate concentrations were found to have up to a 10-fold increase when compared to unburned soils 3 years post-fire (Adkins et al., 2019). Given previous reports, we would expect to see an increase in N with an increase in vegetative burn severity post-fire.

Microbial mineralization and nitrification have been found to both increase and decrease post-fire depending on fire and environmental conditions. The post-fire decrease is attributed to a close linkage between C and N and the resulting loss of C, while the increase is attributed to increases in microbial activity, and C and P inputs (Smithwick et al., 2005). After a 300-day incubation period it was found that there were no differences in mineralization or nitrification rates post-fire (Adkins et al., 2019). However, Su et al. (2022) found a net decrease in N mineralization in fire affected soils and found no significant difference in N nitrification rates. This finding agrees with Kucuk and Kahveci (2020), who found that mineralization of organic N most likely decreases post-fire due to the decrease in soil microbes from intense heating. For example, Gómez-Rey and Gonzalez-Prieto, (2013) found a decrease in nitrification rates due to soil heating reducing nitrifying microbes. Post-fire, significant quantities of nitrates can be removed from the soil root zone due to leaching (Su et al., 2022). Additionally, it has been
reported that nitrification rates increase post-fire, and are dependent upon vegetation type, plant recovery, incurred nutrient uptake, and climatic and topographic conditions (Ball et al., 2010a; Stephens and Homyak, 2023). In contrast, Ibáñez et al. (2022) found no change in mineralization rates due to fire severity four years post-fire but did indicate a reduction in nitrification rates. The reported results on mineralization and nitrification vary depending on fire severity, biome and forest conditions.

Fire reduces soil microbial biomass by up to 96% and species richness by up to 99% which may have effects on nutrient cycling due to the reduction of these soil organisms (Pressler et al., 2019). This decrease in both soil microbe population and microbial respiration has been found in multiple studies (Wang et al., 2012a; Maksimova and Abakumov, 2015; Pellegrini et al., 2021). However, Hu et al. (2020) found that fire significantly increased microbial respiration; this discrepancy is most likely due to differences in soil texture, fire intensity and ecosystem type (Xu et al., 2022a).

Soil pH increases post-fire with fire intensity (Kennard and Gholz, 2001; Scheuner et al., 2004; Pereira et al., 2011; Norouzi and Ramezanpour, 2013). This post-fire increase in pH is most likely due to the denaturation of organic acids when they are introduced to a heat source and the resulting release of basic cations, such as Mg$^{2+}$ and Ca$^{2+}$ (Kennard and Gholz, 2001; Certini, 2003; Notario del Pino et al., 2008; Alcañiz et al., 2018b; Xu et al., 2022a). Ash is also high in CaCO$_3$ concentrations which acts as a liming agent raising soil pH (Ohno and Susan Erich, 1990). Soil pH has been found to be closely linked to SBS and ash deposits. For example, Thomaz (2017) found that as soil heating increased, pH increased in a linear trend starting at 250 °C. At temperatures
below 250 °C, soil pH was not significantly affected, but as temperatures increased up to 550 °C soil pH increased as well.

Soil P has been found to have a significant increase immediately post-fire, with a significant drop in soil P one-year post-fire to below the original P concentrations (Kennard and Gholz, 2001; Alcañiz et al., 2016). This decrease one-year post-fire is most likely due to leaching, erosional losses and plant consumption (Alcañiz et al., 2016). For example, Thomaz (2017) found that soil P did not follow a linear trend when heating at increasing temperatures. Instead, soil P increased until 350 °C and then decreased under slash and burn burning conditions.

Soil extractable cations typically increase post-fire but are impacted to varying degrees by fire severity. For example, potassium (K+) increases immediately post-fire but then decreases to below original concentrations one-year post-fire (Alcañiz et al., 2016), however temperatures need to reach 450 °C for volatilization to occur (Thomaz, 2017). Significant increases in Mg$^{2+}$ and Ca$^{2+}$ were found following low intensity fire in 0-8 cm soil depth. These increases were not as drastic, nor did they last in the soil profile for as long as the increases found post high intensity fire (Kennard and Gholz, 2001). This corroborates with Lewis (1974) who found a drastic increase in divalent cations post-fire.

In a study where samples were taken immediately after the fire and one-year post-fire, it was found that Mg$^{2+}$ and Ca$^{2+}$ had an immediate increase and then returned to prefire conditions after a year (Alcañiz et al., 2016). However, Thomaz (2017) found that Ca$^{2+}$ and Mg$^{2+}$ were not affected by variable burn intensities. Outeiro et al. (2008) reported that divalent cations increased for 3 years post-fire while monovalent cations decreased post-fire. Divalent cations (Mg$^{2+}$ and Ca$^{2+}$) are not as mobile as monovalent cations after
fire and they often exist as hydroxides or carbonates. Meanwhile, monovalent cations (K$^+$ and Na$^+$) are often present as chlorides and carbonates and are mobilized easily (Outeiro et al., 2008).

Ash is an important factor in post-fire soils as it is deposited onto the soil, moves into soil pore spaces, and is high in cations (Bodí et al., 2014b; Chafer et al., 2016; Quigley et al., 2019). The two main classes of ash in wildfire scenarios are black ash and white ash (Quigley et al., 2019). Black ash tends to form in low and medium burn intensities, while white ash is forms in high burn intensities (Chen et al., 2022b). Black ash contains lower concentrations of polyaromatic hydrocarbons and nitrogen containing compounds but has higher concentrations of lignin and phenol compounds than its counterpart, white ash. Due to the higher concentrations of carboxyl carbon in white ash it is more water soluble, indicating that it may be more mobile. This indicates that as burn severity increases aromatic carbon and nitrogen compounds increase and lignin and phenol compounds decrease as the lignin is converted to aromatic compounds as it burns (Chen et al., 2022b). Wildfire ash has increased concentrations of cations such as Ca and Mg (Pereira et al., 2011).

2.5 Mineralogical Impacts:
Ammonium-oxalate extraction dissolves mostly amorphous Fe and Al but does not dissolve crystalline oxides leading to the extraction being used to determine amorphous Fe and Al in soil (Nlckrecue and Der, 1965). Ammonium-Oxalate extractions may also extract crystalline maghemite (Schwertmann, 1958). Goethite, an Fe-oxyhydroxide, is dissolved by citrate-dithionite extractions, but not well by ammonium-oxalate extractions (Slotznick et al., 2020). Unlike the ammonium oxalate extraction, the
citrate-dithionite extraction dissolves much of the crystalline oxides and the amorphous minerals leading to dithionite being used to determine total pedogenic Fe and Al in soils (Nlckrecue and Der, 1965; McKeague, 1966; Carter and Gregorich, 2008; Jordanova et al., 2018). Crystalline Fe and Al may be determined by taking the difference between the total Fe or Al and the amorphous Fe and Al. Sodium-pyrophosphate extractions were found to extract organically complexed Al and Fe leading to sodium-pyrophosphate being used to determine organometal complexes within soil (McKeague, 1966; Carter and Gregorich, 2008).

Some mineralogical changes occur to Fe-oxides during fire. Goethite, which would be present in citrate-dithionite extractable Fe, is transformed between 250-420 °C (Liu et al., 2013). Therefore, the presence of Goethite in high concentrations in post-fire soils indicates that the mineral soil did not exceed these temperatures, or that podzolization occurred post-fire (Jordanova et al., 2018). In areas of intense heat, Goethite can be converted to Hematite or Maghemite (Ulery et al., 2017). This would be extracted in the ammonium oxalate extraction. Mineralogical changes also effect phyllosilicates and CEC, with CEC lost due to the destruction or dehydroxylation of Vermiculite and Chlorite (Ulery et al., 2017). Under high severity burn conditions we expect to see an increase in hematite and maghemite.

2.6 Remotely Sensed Soil Burn Severity:

Currently, the SBS mapping is done by utilizing a Burned Area Reflectance Class (BARC) map. The BARC map is made by using normalized burn ratio (NBR) and differenced normalized burn ratio (dNBR). NBR is derived from the use of near infrared (NIR) and mid-infrared bands (SWIR) taken via Landsat satellite images. The NBR
algorithm is \( NBR = \frac{NIR - SWIR}{NIR + SWIR} \) (Eq. 1, Parsons et al., 2010; Parks et al., 2014). NIR is reflected by green vegetation while SWIR is mostly reflected by rock and soil (Parsons et al., 2010; Parks et al., 2014). The dNBR is the difference between the pre and post-fire images and once derived it is used to create the BARC map by subjectively assigning thresholds to each SBS classification. This map does not yet portray SBS throughout the fire, as it is then modified to create an SBS map based off of field data (Lentile et al., 2006; Safford et al., 2007).

2.7 Remote Sensing and Environmental Covariates:

Remote sensing is the main form of mapping and understanding burn severity from wildfires (Morgan et al., 2014). The quantification of vegetation burn severity is difficult as impartiality while evaluating burn severity changes depending upon the individual and which lens one is looking at burn severity through (Morgan et al., 2014). This makes it difficult to compare vegetation burn severity recordings between literature and researchers. Many different metrics have been used to create remotely sensed vegetative burn severity classifications. Normalized burn ratio (NBR), differenced normalized burn ratio (dNBR), and normalized difference vegetation index (NDVI) are used for remotely sensed vegetation burn severity (Malone et al., 2011; Morgan et al., 2014). A suite of remote sensing tools, from satellite to UAV (drones) with different sensor combinations have been used to generate the spectral signatures and ratios that are used for these classifications.

The NBR is the difference between near infrared (NIR) and short-wave infrared (SWIR) divided by the sum of NIR and SWIR (Eq. 1). It is a classification scheme used
to determine burn severity with high values indicating healthy vegetation and low values indicating more severe burning (Keeley, 2009b). It is useful because the visible to near infrared reflectance is reduced dramatically post-fire due to changes in the composition of the vegetation and soil post-fire allowing the user to “see” the burn severity (Chu and Guo, 2014). The delta normalized burn ratio (dNBR, Eq. 2) is the difference between pre and post-fire NBR values with high values indicating high vegetative burn severity and low values indicating lower burn severity while negative values indicate plant regrowth (Keeley, 2009b). Delta normalized burn ratio values range from -100 to 1300 (they are typically multiplied by 1000) with higher values indicating higher burn severity and negative values indicating regrowth (Ariza et al., 2021). Burned area index (BAI, Eq. 4) is a combination of red and NIR and is used to sense the charcoal signature in post-fire areas to map fires rapidly with higher values (maximum of 1.0) representing higher charcoal signatures and lower values (minimum of -1.0) representing unburned (Pereira et al., 2000; Martín and Chuvieco, 2006). The BAI differs from dNBR and RdNBR as it is only a post-fire image and does not take into consideration the pre-fire conditions. This can be useful if there is no good pre-fire imagery due to cloud or smoke shrouding. Relativized differenced normalized burn ratio (RdNBR, Eq. 3) is similar to dNBR but it normalizes dNBR which allows users to use the same bins for burn severity between fires making it easier to compare burn severity values (Miller et al., 2009). It normalizes dNBR by dividing by the square root of the absolute value of the prefire NBR (Miller et al., 2009). The RdNBR follows the same format and range as dNBR with higher values indicating higher burn severity (Miller et al., 2009). Normalized burn ratio thermal (NBRT, Eq. 5) is similar to NBR but includes the thermal band as well and is only taken
as a post-fire image (Holden et al., 2005). By including the thermal band one can identify the post-fire thermal reflectance which often increases in areas of high plant mortality (Pacheco et al., 2023). NBRT ranges from -1.0 to 1.0 with higher values indicating higher burn severities (Verma et al., 2022).

\[
\begin{align*}
NBR &= \frac{(NIR - SWIR)}{(NIR + SWIR)} \\
\text{dNBR} &= \text{Prefire NBR} - \text{Postfire NBR} \\
RdNBR &= \frac{\text{dNBR}}{\sqrt{\text{ABS}(\text{PreFire NBR}/1000)}} \\
BAI &= \frac{1}{((0.1 - R)^2 + (0.06 - NIR)^2} \\
NBRT &= \frac{\text{NIR} - \text{SWIR (Thermal}/1000)}{\text{NIR} + \text{SWIR (Thermal}/1000)}
\end{align*}
\]

Other non-fire specific remote sensing covariates may be used to remotely sense vegetation attributes. The normalized differenced vegetation index (NDVI, Eq. 6) measures the quantity and health (or “greenness”) of vegetation in an area using the NIR and red bands (Banday et al., 2019). It does this by leveraging the idea that red light is absorbed by the chlorophyll pigment in plants that are healthy allowing users to measure both vegetation density and health by utilizing NDVI (Pastor-Guzman et al., 2015; Dutta Gupta et al., 2021; Huang et al., 2021). Higher values indicate healthier, or less water stressed plants while lower values indicate less healthy, or sparser vegetation (Drisya et al., 2018; Banday et al., 2019). The normalized differenced water index (NDWI, Eq. 7) is similar to NDVI but senses the water content within vegetation canopies utilizing the NIR band instead of red band as NDVI does (Gao, 1996a). For the NDWI higher values indicate higher water content in leaves. The enhanced vegetation index (EVI, Eq. 8) is
another remotely sensed variable for the measurement of vegetative health with higher values generally indicating healthier vegetation. However, EVI corrects for background noise and is more sensitive in areas of heavier vegetation (Jiang et al., 2008). Due to its correction for background noise, it is much more complicated than NDVI, which is based off of (Matsushita et al., 2007).

\[
NDVI = \frac{(NIR - R)}{(NIR + R)}
\]  
\[
NDWI = \frac{(G - NIR)}{(G + NIR)}
\]  
\[
EVI = \frac{(g \times (NIR - R))}{(NIR + C1 \times R - C2 \times B + L)}
\]

\[g = \text{gain factor}\]
\[C1 \& C2 = \text{aerosol coefficients}\]
\[L = \text{Canopy Background}\]

2.8 Digital Soil Mapping and the Soil Landscape Relationship:

Digital soil mapping (DSM) has been on the rise since the 1990’s and has seen a large amount of growth in the past few years. It is used to predict soil properties using raster based environmental covariates and statistical modeling (Savin et al., 2019). These environmental covariates are derived using the SCORPAN equation. The equation for SCORPAN is as follows Soil = f(Soils Data, Climate, Organisms, Relief, Age, Parent Material, and N is for spatial distribution) (McBratney et al., 2003). The SCOPRAN equation is derived from Jenny’s (1941) CLORPT (Soil= f(Climate, Organisms, Relief, Parent Material and Time) model for soil synthesis. However, it includes a spatial location (distance between observations) and legacy soils data. Since the inputs are typically raster based, as opposed to expert based, it is explicitly quantitative as opposed to the inherently qualitative, but very useful, CLORPT based soil landscape model.
(Jenny, 1941; McBratney et al., 2003). The basic premise of DSM is that one can utilize soil point data in combination with covariates derived following the SCORPAN model and statistical learning to predict soil characteristics and create a soil map (Zhang et al., 2017). The largest changes in soil mapping with the SCORPAN model is the addition of spatial data (e.g. coordinates), the use of spatial autocorrelation to drive modeling, and the incorporation of explicit quantitative soil relationships (McBratney et al., 2003). By incorporating these ideas in DSM, they allow one to utilize models that include the factor of space and create continuous soils maps which has changed soil mapping by creating higher resolution and more accurate soils maps (Sanchez et al., 2009). Although less common, DSM allows for models that not only predict, but can allow the user to gain new understandings of how the soil forming factors influence the distribution of soil properties, and how the soil forming factors are intertwined and interdependent (Eger et al., 2021).

Soil properties such as SOC, pH, nitrates, Fe-oxides and cations have been mapped globally utilizing digital soil mapping (Sanchez et al., 2009). A study in Norway modeling SOC was able to explain up to 63% of the spatial variability in SOC utilizing various remotely sensed covariates and found the most important covariates to be precipitation, terrain wetness index and elevation (Adhikari et al., 2014). A review on digital soil mapping of SOC found that organism variables are the most important with climate and topography being the second and third most important (Lamichhane et al., 2019b). Exchangeable Ca\textsuperscript{2+} was mapped with an R\textsuperscript{2} of up to 0.82 in sugarcane fields however, to do this the researchers utilized field validated EC values in the model indicating that utilizing other soil properties, and not just remotely sensed covariates,
helps in the prediction of soil cations (Li et al., 2019). Meanwhile, Sharififar (2022) utilized only remotely sensed data (Landsat imagery and a Digital Elevation Model (DEM)) was able to explain 46% of the variance in exchangeable Ca\(^{2+}\). Soil nitrates have also successfully been mapped (Wade et al., 1996) with strong correlations between land use, and Landsat band 1 (Lamsal et al., 2009; Gopp et al., 2017). For soil mineralogy, both Novais et al. (2021) and Mendes et al. (2022) have mapped Fe-oxides utilizing machine learning models. For example, Mendes et al. (2022) utilized random forest (and other ML models) models and SCORPAN style covariate selection finding that environmental and topographic covariates were important in the spatial distribution of Fe-oxides. The use of SCORPAN style DSM models has led to the inference and prediction of soil properties from remote sensing and statistical modeling.

Climate is extremely important in both the understanding and prediction of soil health and soil formation, as it is an important driver of spatial variability. Increased precipitation increases water flow throughout soils. As water flows through soil, it leaches cations and translocates them down the soil profile leading to more acidic soils (Shi et al., 2018). Monovalent cations, such as K\(^+\) and Na\(^+\) are sensitive to leaching indicating that high precipitation rates will lead to reduced levels of K\(^+\) and Na\(^+\) (Lehmann and Schroth, 2003). Precipitation data may be gathered from the closest meteorological station, or the Precipitation-elevation Regression on Independent Slopes Model (PRISM) data may be applied (Maynard and Levi, 2017). These PRISM data are created utilizing regression techniques and DEM’s to spatially predict precipitation over various time periods (Daly et al., 1994). Temperature can increase the weathering rate of parent material and the release of soil cations from the parent material (Jenny, 1941;
Povak et al., 2014). Climate variables have been shown to have a strong correlation with soil properties within a DSM context (Sun et al., 2023) leading to climate variables often being leveraged for the prediction of soil properties (Chen et al., 2022a).

Similar to climate, topography dramatically affects the spatial variability of soil properties. Clay distribution is affected by topography with higher clay concentrations present at the base of toe slopes and lower concentrations present at ridge lines. This in turn affects CEC, and soil pH (Khomo et al., 2011). For example, Jafari et al. (2012) found areas with high topographical influence have more accurate predictions for the mapping of soils than areas where topography is not as extreme of an influence. Terrain attributes generally have the simplest quantitative relationships found in DSM (McBratney et al., 2003). Topography has been found to be more important than climatic covariates for the prediction of soil C, indicating the importance of including topographical attributes within DSM models (Schillaci et al., 2017). Parent material is also an important factor in the determination of soil type, texture, and properties (Jenny, 1941; Mello et al., 2021). It is possible to use parent material in remote sensing applications, but it is difficult to find fine enough resolution maps to make them useful (Bonfatti et al., 2020).

2.9 Statistical Analysis:
Sampling techniques can play a large role in how well statistical analyses describe the variability of a target population. One of the most common methods for DSM is stratified random sampling; a sampling strategy in which strata are defined and then simple random sampling is introduced for each stratum. This method assures that each strata has a point, or multiple within as opposed to simple random sampling (Gruijter et
Another form of stratified random sampling is Conditional Latin Hypercube Sampling (CLHS) which stratifies by environmental covariates (Yang et al., 2020; Ma et al., 2020). Sampling density can also affect the statistical computation of one’s samples. Yang et al. (2020) found that the optimal soil sample density using CLHS is 10.06 samples/km$^2$. Furthermore, Mcbratney and Pringle (1999) also found that spatial autocorrelations between soil properties were present below 500 m. This indicates that as sample density decreases, prediction accuracy also decreases as variability of the predicted property is smoothed out (Grunwald, 2009). CLHS also allows for fewer samples to be taken, or for each sample to cover more variability in the environmental covariates used for stratification, which has led to CLHS becoming popular for many DSM techniques (Zhang et al., 2017; Brus, 2019).

Spatial resolution of covariates is an important factor in digital soil mapping for the understanding of soil characteristics as it affects many things such as statistical significance, computation speed of the models, and size of the covariates. Spatial resolution has been found to influence models; however, the effect may be relatively small if the model is already a good indicator of the modeled soil property. If the model is not a good predictor, more detailed covariates will have a larger influence on the model (Miller et al., 2015; Samuel-Rosa et al., 2015). Miller et al. (2014) found that by combining multi-scale data one could improve R-squared values in DSM models by up to 70%, which corroborates with other studies (Behrens et al., 2014). They also found that reducing the number of covariates used in a model often led to better results as some modeling systems cannot be trusted to find the best covariates (Miller et al., 2015).
2.10 DSM Modeling Techniques and Machine Learning Algorithms:

Multiple modeling techniques have been used in DSM. All of these include the use of soil point data and environmental covariates. The most common techniques are kriging, random forest, cubist, extreme gradient boosting, multi-linear models, neural networks and hybrid approaches which include multiple of the modeling techniques (Zhang et al., 2017). Kriging, an area of geostatistics developed in the 1950’s that follows the fundamental rules of spatial autocorrelation; the idea that direction and distance from an object can be used to explain variation and that variance between two objects increases with distance (Krige, 1951; Daya Sagar et al., 2018). This relationship is defined using a semivariogram model. This model influences how much weight points will have on each prediction; models with a steeper curve will allow points that are closer to the prediction to have more weight and ones that are further away will have less. There can also be a distance cutoff for when points can no longer influence the prediction (López-Granados et al., 2002; Chilès and Desassis, 2018).

Machine learning algorithms lead to the best predictions but can also be black boxes for interpretation or causal relationship between SCORPAN factors and target soil properties. Common DSM machine learning algorithms include random forest, cubist and extreme gradient boosting. Cubist modeling is a form of machine learning that utilizes rule-based modeling by fitting linear models to predictor data that has been subset, and then creates a new node for each of the linear models. One of its main principles is the theory of Occam’s razor (John et al., 2021b), a principle that states that the model that can explain the same amount of variation as another, but with fewer predictors is the superior model (Batty and Torrens, 2005). Random forest (RF) is one of the most utilized modeling techniques in DSM as it is efficient, reduces noise and overfitting and is
relatively easy to interpret (Rahbar Alam Shirazi et al., 2024; Siqueira et al., 2024). It is an ensemble method, a tree-based algorithm that uses multiple non correlated trees and combines them together to create one model (Siqueira et al., 2024). The model then picks the average output of all the trees with the main idea being that the average of the trees will give the correct output (Breiman, 2001). Extreme gradient boosting is also an ensemble-based learning method, meaning that it uses multiple methods to learn. It combines both decision trees and boosting together by using the decision tree as a weak predictor (Chen and Guestrin, 2016). Each tree is then designed to have variable weighting and learns from the previous tree. This is how it differs from random forest, as random forest has all trees weighted equally (Rahbar Alam Shirazi et al., 2024).

2.11 Multivariable Linear Regression and Variable Reduction:

One can also use multi-variable linear regression models (MLR) to infer the relationship between environmental covariates and soil properties. In other words, an MLR model can be created to understand the linear relationship between environmental covariates and a chosen soil property allowing the user to individually analyze the magnitude and effect of each covariate on a soil property (Rosales Heredia et al., 2011; Samuel-Rosa et al., 2015; Forkuor et al., 2017; John et al., 2021a). This method also works well when there is not enough spatial correlation between sample points, or not enough sample points to implement spatial correlation techniques (Moraes et al., 2018). However, due to the nature of linear models, they are not able to model non-linear relationships which can be exceptionally limiting when the response or explanatory variables have a non-linear relationship (Forkuor et al., 2017).
StepAIC is often used as a part of MLR modeling to reduce the number of covariates in a model using Akaike’s information criterion (AIC) and a stepwise procedure (Poggio et al., 2013). AIC determines the model that is the most accurate with the lowest complexity. It does this by penalizing models with more complexity (Akaike, 1973). StepVIF is used to solve a major problem with many multivariable linear models, the problem of multicollinearity. Multicollinearity is the idea that two or more covariates are correlated, the interpretation of regression coefficients is unreliable (John et al., 2021a). The stepVIF function from the Pedometrics package in RStudio is designed to reduce collinearity within models (Rosa-Allesandro, 2022). It does this by creating a model with VIF values below a specific threshold by a stepwise procedure that is based upon generalized variance inflation factors (Rosa-Allesandro, 2022).
3.1 Site Description and Experimental Design:

This study was conducted in the Little Creek watershed (Davenport, California) in the Santa Cruz mountains, part of California Polytechnic-San Luis Obispo’s Swanton Pacific Ranch (Figure 1). The Little Creek watershed is approximately 500 hectares and is predominantly a *Sequoia sempervirens* (redwood) and *Pseudotsuga menziesii* (Douglas fir) ecosystem and has an average temperature of 13.6 °C and average precipitation of 65.25 cm (CIMIS, 2022). It is set in a Mediterranean climate with dry, warm summers and moist, cool winters (Lancaster et al., 2020) and is primarily second growth forest. The area is part of the Coast Range physiographic province of California, which was formed by plate tectonic forces associated with the San Andreas Fault system. The Little Creek drainage encompasses a diverse topography and geologic features, including marine coastal terraces, alluvial valleys, steep foothills and mountains (CalFire WERT, 2020). The parent material of the area is a Salinian basement complex of granitic and metasedimentary rocks, with Franciscan formation sandstones, mudstones and greywacke (Clark, 1982). The dominant soil types in the Little Creek drainage are mapped as the Ben Lomond Castelli-Sur complex, the Santa Lucia channery clay loam and the Maymen rock outcrop complex along the ridges. Soil texture in the area is dominated by sandy loam, loam, clay loam, and clay soils based on SSURGO data from Santa Cruz County (NRCS, 2023).

The Little Creek drainage burned in the CZU Complex fire in 2020 and the Lockheed fire in 2009, with almost the entirety of the Little Creek drainage being burnt
during both fires (CalFire, 2009, 2020). Figure 1 shows soil burn severity (SBS) ratings of the CZU Complex for the Little Creek drainage and associated areas. The CZU Lightning Complex consisted of multiple lightning-ignited fires throughout San Mateo and Santa Cruz counties with Santa Cruz County being predominantly affected by the fire (CalFire WERT, 2020). The CZU Lighting Complex fire started on August 16, 2020, due to a severe thunderstorm, and was fully contained on September 22, 2020. There was a total of 86,509 acres burned, 1,450 structures lost, and one casualty (Lancaster et al., 2020). The area burned by the CZU Lighting Complex was composed of various types of ownership, including federal, state, non-profit, and private landholdings (CalFire WERT, 2020; Lancaster et al., 2020). The current land use of the burned area of the CZU Lightning Complex Fire is recreational and private timber resources (CalFire WERT, 2020).
Figure 1: Site map of Little Creek showing collection points with Cal Fire WERT SBS with outlines of studied drainages. Little Creek drainage is the northernmost drainage. Winter Creek drainage is the southwestern most drainage and Archibald Creek is the southeastern drainage.
3.2 Environmental Covariates:

Remotely sensed environmental covariates were determined for use as proxies for the soil forming factors in digital soil mapping (DSM) framework, and for use as stratification variables for sample design (McBratney et al., 2003). In addition, we included rasters that represent fire’s effects to ecosystems, and combined them with DSM SCORPAN (Soil = f(Soils data, Climate, Organisms, Relief, Parent material, and N is for spatial distribution)) factors, to elucidate fires effects on soil properties (McBratney et al., 2003). These covariates were determined using available literature and expert knowledge of soil and fire to help spatially predict soil properties utilizing Random Forest (RF) algorithms and Multiple Linear Regression (MLR). Before use in RF and MLR, environmental covariates were statistically analyzed for each soil property and either accepted or rejected to ensure parsimony and that the chosen covariates created the most statistically accurate model as different covariates may be better for the inference of soil properties than others.

3.2.1 Terrain and Vegetation Covariates:

All terrain analyses were derived using a Digital Elevation Model (DEM) with the 30 m National Elevation Dataset (NED) as this is open source and widely available within North America (Gesch et al., 2018). Terrain covariates were used due to terrain’s effects on both soil formation and fire behavior. Slope, aspect, roughness, terrain position index (TPI) and terrain roughness index (TRI) were derived using the Terra package in R (R Core Team, 2022; Robert and Hijmans, 2023). McNab curvature was derived using the SpatialEco package in R and confines the view of the curvature analysis to a 3 X 3 image when creating curvature (Mcnb, 1992; Murphy and Ram, 2022). Flow accumulation and flow direction analysis utilized the Whitebox tools package in RStudio.
Vegetation covariates normalized differenced vegetation index (NDVI, Eq. 1), normalized differenced wetness index (NDWI, Eq. 2), and enhanced vegetation index (EVI, Eq. 3) were derived using Google Earth Engine for a Landsat 32-day composite corresponding to July 2020 to acquire pre-fire vegetation data.

### 3.2.2 Fire covariates:

Fire covariates were determined by using a mixture of covariates that were commonly used ones that were thought to illicit better soil responses. Relative differenced normalized burn ratio (RdNBR, Eq. 6), differenced normalized burn ratio (dNBR, Eq. 5) and normalized burn ratio (NBR, Eq. 4) were derived in ArcPro (ESRI, 2023). The dNBR is a measure of burn severity with low values indicating low burn severity and high values indicating high burn severity and is one of the most used burn severity metrics (Miller et al., 2009). The bins for burn severity classification go as such; unburned (-100-99) low burn severity (100-269), moderate burn severity (270-659), and high burn severity (660-1300) (Ariza et al., 2021). Figure 2 indicates a large portion of collected points were from areas with relative higher burn severity. RdNBR is newer version of dNBR that theoretically normalizes the dNBR values and removes the biasing affects from the prefire images (Miller et al., 2009). Burned area index (BAI, Eq. 7) and normalized burn ratio thermal (NBRT, Eq. 8) were extracted in Google Earth Engine for a 32-day composite corresponding to November 2020 to acquire post-fire burn data.

November 2020 was chosen due this being immediately post-fire and typically remotely sensed burn images are taken as close to the fire as possible to avoid inference between other factors such as ash translocations due to wind and rain (Parsons et al., 2010). BAI and NBRT were included as they use different wavelengths than dNBR and RdNBR to
measure burn severity (Filipponi, 2018). Climate data was from the Parameter-Elevation Relationships on Independent Slopes Model (PRISM) (PRISM Climate Group, 2022). All covariates were resampled to 30 m pixels. SBS comes from CalFire WERT (Watershed Emergency Response Team) as an expert validated form of SBS (CalFire WERT, 2020). Rasters of environmental covariates were collocated with soil sample locations to extract explanatory variables from the raster stack for subsequent use in modeling routine.

![Figure 2: Histogram of dNBR at point locations of collected samples.](image)

\[
NBR = \frac{(NIR - SWIR)}{(NIR + SWIR)} \tag{1}
\]

\[
dNBR = \text{Prefire NBR} - \text{Postfire NBR} \tag{2}
\]

\[
RdNBR = \frac{dNBR}{\sqrt{ABS(PreFire NBR/1000)}} \tag{3}
\]

\[
BAI = \frac{1}{((0.1 - R)^2 + (0.06 - NIR)^2} \tag{4}
\]

\[
NBRT = \frac{NIR - SWIR (\text{Thermal}/1000)}{NIR + SWIR (\text{Thermal}/1000)} \tag{5}
\]
\[ \text{NDVI} = \frac{\text{NIR} - R}{\text{NIR} + R} \]  
\[ \text{NDWI} = \frac{\text{G} - \text{NIR}}{\text{G} + \text{NIR}} \]  
\[ \text{EVI} = \frac{g \times (\text{NIR} - R)}{\text{NIR} + C1 \times R - C2 \times B + L} \]

\( g = \text{gain factor} \)
\( C1 \ & \ C2 = \text{aerosol coefficients} \)
\( L = \text{Canopy Background} \)

3.3 Soil sampling and Field Data Collection:

With the intention of combining factors of soil formation with fire effects to soils, we utilized topographic (slope) and vegetation (pre-fire NDVI) variables, along with dNBR and existing SBS mapping, to stratify the Little Creek watershed via conditional Latin hypercube (CLHS) for sampling (Minasny and McBratney, 2006). SBS was chosen due to it being an expert validated form of burn severity and because it is the only available SBS data (Figure 1). This method leverages the idea of stratified random sampling but utilizes the distribution of pixels in each raster to identify best sampling locations, maximizing coverage across the distribution of values in the predictor space (Yang et al., 2020; Ma et al., 2020). A small group of samples were utilized for modeling (n=12) that were collected in plot centers of an unrelated post-fire erosion study. The collected samples from the erosion plots were in varying enough terrain and all burn severities that
it was decided they would not produce sample bias. These soil samples were used to bolster the sample size in the project.

Two depths were collected at 79-point locations, 0-2.5 cm and 2.5-5 cm. Samples were taken at varying depths due to the heat pulse from the fire affecting soils at a reduced rate as the heat pulse travels down the profile. Because the fire effects tend to be constrained to the soil surface (Badía-Villas et al., 2014), it is assumed that the lower depth will have reduced fire effects. Soil samples were collected 1-year post-fire in the summer of 2021 to gather post-fire soil effects. Samples were collected 1-year post-fire as we were unable to access the area until then due to safety concerns such as falling snags. Ash was scraped away, and soil was sampled in the two depth increments using a bulk density core. General soil samples were collected at the same location as bulk density samples using a trowel (n=79). Due to cost and sample timing, soil cations were only analyzed for the 66 samples originally collected for this study, and not the additional samples collected from the erosion study. A total of 78 samples were analyzed for total C/N due to a missing sample. All other analyses used the total 79 samples. Soils were sieved to 8 mm and air dried for subsequent analysis upon return from the field. All data are reported on an airdried basis.

3.4 Soil Analyses:

A suite of soil properties was analyzed that were believed to be able to be spatially predicted via remote sensing capabilities and also affected by fire. This was done in order to infer remotely sensed burn severity metrics (i.e. dNBR) correlation to these soil properties.
3.4.1 Physical Soil Properties:

Bulk density (BD, g cm$^{-3}$) was determined using a core sampler, and adjusted for rock content fragments (Abed et al., 2018). Water holding capacity was determined on 10 g sub samples (Dexter and Bird, 2001).

3.4.2 Soil Chemical Properties:

Ammonium acetate was used to determine sulphate and exchangeable cations for K, Mg, Ca and Na (USDA, 2022). These are referred to as $K_{ex}$, $Mg_{ex}$, $Ca_{ex}$, and $Na_{ex}$ within this study. Cation exchange capacity (CEC) was computed using the sum of the cations and extractable acidity (USDA, 2022). Available P was determined following the Olsen P methodology (Olsen, 1954). All analyses utilized a Horiba, Ultima 2 Inductively Coupled Plasma – Optical Emission Spectrometer (ICP-OES) (Horiba, France). For soil pH a saturated paste solution was used utilizing an epoxy filled Thermo Fisher Scientific Orion pH probe (Massachusetts, US) (USDA, 2022).

3.4.3 Selective Dissolution:

Fe and Al pools were analyzed using acid ammonium-oxalate ($Fe_{o}$, $Al_{o}$), sodium-pyrophosphate ($Fe_{p}$, $Al_{p}$) and dithionite-citrate extractions ($Fe_{d}$, $Al_{d}$) (USDA, 2022). The ammonium oxalate extraction was used to determine amorphous Fe and Al that arise from organic complexes such as amorphous Fe-(hydr)oxides and amorphous aluminosilicates. Sodium-pyrophosphate extraction was used to determine organometal complexes. Dithionite-citrate was used to quantify total free Fe and Al. This includes both organic complexes and organometal complexes. The Horiba, Ultima 2 ICP-OES was used to analyze all extracts (Horiba, France). Crystalline Fe and Al fractions were determined by taking the difference between the total Fe/Al and amorphous Fe/Al (ie. Crystalline Fe= $Fe_{d}$- $Fe_{o}$).
3.4.4 Soil C Dynamics and Soil Health Indicators:

Total C and N were determined using a Vario Max CNS elemental analyzer (Elementar, Langenselbold, Hesse, Germany). Permanganate Oxidizable Carbon (POXC) was determined using 2 M Potassium Permanganate reacted with 2.5 g of soil and analyzed colorimetrically (USDA, 2022).

We determined potentially mineralizable C (Min C) via 48-hr incubation at 50% water holding capacity, and report as CO₂ concentration per hour (mg CO₂-C kg⁻¹ soil hr⁻¹) (USDA, 2022). For potentially mineralizable N (PMN), samples were wet to 50% water holding capacity and incubated for 28-days, with KCL extraction and colorimetric analysis of NO₃⁻ and NH₄⁺ at days 0, 7 and 28 (Stanford and Smith, 1972). The 0, 7 and 28 day NO₃⁻ and NH₄⁺ values were used to calculate net mineralization and nitrification (eq. 10-13).

\[
\text{Net Nitrification 0-7 days} = \frac{\text{Nitrate-N}_{day7} - \text{Nitrate-N}_{day0}}{7 \text{ days}}
\]
\[
\text{Net Nitrification 7-28 days} = \frac{\text{Nitrate-N}_{day28} - \text{Nitrate-N}_{day7}}{21 \text{ days}}
\]
\[
\text{Net Mineralization 0-7 days} = \frac{(\text{Ammonium-N + Nitrate-N})_{day7} - (\text{Ammonium-N + Nitrate-N})_{day0}}{7 \text{ days}}
\]
\[
\text{Net Mineralization 7-28 days} = \frac{(\text{Ammonium-N + Nitrate-N})_{day28} - (\text{Ammonium-N + Nitrate-N})_{day7}}{21 \text{ days}}
\]

3.5 Statistical Analysis:

3.5.1 Multivariable Linear Models:

Multivariable linear models were utilized for statistical analyses to infer the influence of watershed scale explanatory environmental covariates on soil properties (eq.
Soil properties analyzed at each spatial location were the response, and environmental variables extracted from the raster stacks were the explanatory variables.

\[ Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots + \beta_n X_n \]  

A Shapiro-Wilks test was used to assure the normality of residuals fit assumptions. Residuals vs. fitted plot, normal Q-Q plot, scale-location plot and residuals vs. leverage plot were also visually assessed to determine statistical assumptions were met. A linear model was run for each soil property and then passed into two stepwise procedures to generate the most parsimonious model, and to reduce collinearity. We utilized StepAIC() (eq. 15) through the MASS package in RStudio to reduce model complexity and StepVIF() (eq. 16) through the Pedometrics package in RStudio to reduce model collinearity (Ripley et al., 2023; Samuel-Rosa, 2022).

\[ AIC = 2k - 2 \ln(L) \] 
\[ k = \text{number of estimated parameters in model} \] 
\[ L = \text{maximum value of the likelihood value of the model} \] 

\[ VIF = \frac{1}{1 - R^2} \]  

StepAIC reduces the number of covariates in a model using Akaike’s information criterion (AIC) and a stepwise procedure (Poggio et al., 2013). AIC determines the model that is the most accurate with the lowest complexity. It does this by penalizing models with more complexity (Akaike, 1973). Stepwise VIF models create generalized variance inflation factors (VIF), a measurement of variance of one variable with its correlation to another independent variable in the model and uses a forward and backward stepwise procedure to reduce the VIF value for the total model to below 10 (Rosa-Allesandro,
All statistical analysis was done using RStudio (R Core Team, 2022). Once models were created, they were assessed by analyzing p-values, $R^2$ values, and the F-statistic.

In addition to MLR, a nonlinear nonparametric technique, RF was utilized to infer the effect of environmental predictor variables on the soil properties analyzed. Random forest is a tree-based algorithm that uses multiple non correlated trees and combines them together to create one model. The model then picks the average output of all the trees. The main idea is that the average of the trees will give the correct, or at least closest output of the theoretical value to the real value (Breiman, 2001). RF models were run utilizing the Caret package in R (Kuhn et al., 2022; R Core Team, 2022). RF models included all covariates mentioned above. K-fold validation was utilized during this process and RMSE and $R^2$ values were used as validation metrics. The models with highest the $R^2$ and lowest RMSE were chosen for analyses. The K-fold validation process was trained on k-1 of the model and validated on the kth part of the model (Shahrokh et al., 2023). For this experiment 10 folds were created, and the process was repeated 3 times as this reduces bias and variance (Wong and Yeh, 2019).
4.1 Overview of Soil Properties and Models:

Summary results from soil analyses are presented in Table 5 and a summary of model results are presented in Table 6. Key properties are total C and N, mineralizable C, extractable cations, nitrate, ammonium and oxalate extractable Fe, Al and P as they are discussed in extensive detail further in this report. The mean total carbon (C_{total}) and nitrogen (N_{total}) content in the sample soils were 5.9% and 0.3% respectively, giving a C:N ratio of almost 20:1 (Table 1). Mineralizable carbon had a mean of 165.2 mg/kg/day CO$_2$. For extractable cations, the mean concentrations were 304.6 ppm for soil potassium (K$_{ex}$), 267.3 ppm for soil extractable magnesium (Mg$_{ex}$), 2270.7 ppm for soil extractable calcium (Ca$_{ex}$), and 29.0 ppm for soil extractable sodium (Na$_{ex}$) (Table 1). Oxalate extractable iron (Fe$_O$) was 44.8 ppm, oxalate extractable Al (Al$_O$) was 35.2 ppm and oxalate extractable P (P$_O$) was 9.1 ppm (Table 1). Mean soil nitrate concentrations were 0.0049 mg/kg and ammonium concentrations were 0.1134 mg/kg.
Table 1: Descriptive Statistics of Soil Characteristics at Study Site

<table>
<thead>
<tr>
<th>Soil Property</th>
<th>N</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Bulk Density (g/cm³)</strong></td>
<td>82</td>
<td>0.8</td>
<td>0.3</td>
<td>0.3</td>
<td>1.5</td>
</tr>
<tr>
<td><strong>Total C (%)</strong></td>
<td>78</td>
<td>5.9</td>
<td>2.2</td>
<td>1.8</td>
<td>12.1</td>
</tr>
<tr>
<td><strong>Total N (%)</strong></td>
<td>78</td>
<td>0.3</td>
<td>0.1</td>
<td>0.1</td>
<td>0.9</td>
</tr>
<tr>
<td><strong>Mineralizable Carbon (Mg/Kg/Day CO₂)</strong></td>
<td>78</td>
<td>165.2</td>
<td>89.7</td>
<td>21.6</td>
<td>425.1</td>
</tr>
<tr>
<td><strong>Olsen P (ppm)</strong></td>
<td>66</td>
<td>38.9</td>
<td>28.4</td>
<td>4.7</td>
<td>194.6</td>
</tr>
<tr>
<td><strong>pH</strong></td>
<td>66</td>
<td>6.5</td>
<td>0.8</td>
<td>4.5</td>
<td>7.6</td>
</tr>
<tr>
<td><strong>Extractable K (ppm)</strong></td>
<td>66</td>
<td>304.6</td>
<td>125.4</td>
<td>102.7</td>
<td>816.0</td>
</tr>
<tr>
<td><strong>Extractable Mg (ppm)</strong></td>
<td>66</td>
<td>267.3</td>
<td>126.5</td>
<td>27.6</td>
<td>694.4</td>
</tr>
<tr>
<td><strong>Extractable Ca (ppm)</strong></td>
<td>66</td>
<td>2270.4</td>
<td>1114.6</td>
<td>442.0</td>
<td>4819.0</td>
</tr>
<tr>
<td><strong>Extractable Na (ppm)</strong></td>
<td>66</td>
<td>29.0</td>
<td>17.3</td>
<td>8.4</td>
<td>97.8</td>
</tr>
<tr>
<td><strong>CEC (Sum of Cations, cmolc/kg)</strong></td>
<td>66</td>
<td>15.7</td>
<td>5.4</td>
<td>3.5</td>
<td>27.9</td>
</tr>
<tr>
<td><strong>Total S (ppm)</strong></td>
<td>66</td>
<td>19.0</td>
<td>22.0</td>
<td>3.8</td>
<td>173.4</td>
</tr>
<tr>
<td><strong>POXC (mg/kg)</strong></td>
<td>79</td>
<td>1435.9</td>
<td>32.3</td>
<td>1325.4</td>
<td>1521.2</td>
</tr>
<tr>
<td><strong>Oxalate Extractable Al (ppm)</strong></td>
<td>79</td>
<td>35.2</td>
<td>18.4</td>
<td>11.3</td>
<td>110.7</td>
</tr>
<tr>
<td><strong>Oxalate Extractable Fe (ppm)</strong></td>
<td>79</td>
<td>44.8</td>
<td>15.2</td>
<td>13.2</td>
<td>87.4</td>
</tr>
<tr>
<td><strong>Oxalate Extractable P (ppm)</strong></td>
<td>79</td>
<td>9.1</td>
<td>5.5</td>
<td>1.7</td>
<td>25.9</td>
</tr>
<tr>
<td><strong>Oxalate Extractable Si (ppm)</strong></td>
<td>79</td>
<td>9.0</td>
<td>6.7</td>
<td>1.7</td>
<td>39.4</td>
</tr>
<tr>
<td><strong>Pedogenic Al (Dithionite-Oxalate, ppm)</strong></td>
<td>80</td>
<td>2114.2</td>
<td>1019.0</td>
<td>585.1</td>
<td>4943.8</td>
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<tr>
<td><strong>Pedogenic Fe (Dithionite-Oxalate, ppm)</strong></td>
<td>80</td>
<td>12529.4</td>
<td>5312.8</td>
<td>4210.5</td>
<td>36538.5</td>
</tr>
<tr>
<td><strong>Dithionite Extractable Mn (ppm)</strong></td>
<td>80</td>
<td>627.6</td>
<td>773.2</td>
<td>14.8</td>
<td>4075.3</td>
</tr>
<tr>
<td><strong>Dithionite Extractable P (ppm)</strong></td>
<td>80</td>
<td>598.8</td>
<td>269.5</td>
<td>192.5</td>
<td>1469.6</td>
</tr>
<tr>
<td><strong>Dithionite Extractable Si (ppm)</strong></td>
<td>80</td>
<td>957.1</td>
<td>330.7</td>
<td>385.8</td>
<td>1905.5</td>
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<tr>
<td><strong>Organically Complexed Al (ppm)</strong></td>
<td>80</td>
<td>24.6</td>
<td>20.4</td>
<td>3.0</td>
<td>123.2</td>
</tr>
<tr>
<td><strong>Organically Complexed Fe (ppm)</strong></td>
<td>80</td>
<td>20.8</td>
<td>11.2</td>
<td>4.5</td>
<td>50.5</td>
</tr>
<tr>
<td><strong>Organically Complexed Mn (ppm)</strong></td>
<td>80</td>
<td>4.2</td>
<td>3.7</td>
<td>0.1</td>
<td>19.5</td>
</tr>
<tr>
<td><strong>Organically Complexed Si (ppm)</strong></td>
<td>80</td>
<td>25.4</td>
<td>35.9</td>
<td>0.0</td>
<td>196.1</td>
</tr>
<tr>
<td><strong>Mineralizable Carbon (ppm)</strong></td>
<td>80</td>
<td>163.7</td>
<td>88.3</td>
<td>21.6</td>
<td>425.1</td>
</tr>
<tr>
<td><strong>Nitrate (mg/kg)</strong></td>
<td>80</td>
<td>0.005</td>
<td>0.0144</td>
<td>0</td>
<td>0.0144</td>
</tr>
<tr>
<td><strong>Ammonium (mg/kg)</strong></td>
<td>80</td>
<td>0.113</td>
<td>0.4415</td>
<td>0</td>
<td>0.4415</td>
</tr>
<tr>
<td><strong>7-Day Net Nitrification (mg/kg/day)</strong></td>
<td>80</td>
<td>-0.001</td>
<td>0.031</td>
<td>-0.022</td>
<td>0.031</td>
</tr>
<tr>
<td><strong>7-Day Net Mineralization (mg/kg/day)</strong></td>
<td>80</td>
<td>-0.001</td>
<td>0.009</td>
<td>-0.009</td>
<td>0.009</td>
</tr>
</tbody>
</table>
Table 2: Model comparison of random forest (RF) and multivariable linear model (MLR) for all soil properties reported with $R^2$ Adjusted and Root Mean Square Error (RMSE)

<table>
<thead>
<tr>
<th>Soil Property</th>
<th>Model</th>
<th>$R^2$ Adjusted</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_{total}$</td>
<td>MLR***</td>
<td>0.37</td>
<td>0.34</td>
</tr>
<tr>
<td></td>
<td>RF</td>
<td>0.32</td>
<td>1.84</td>
</tr>
<tr>
<td>$N_{total}$</td>
<td>MLR***</td>
<td>0.29</td>
<td>0.12</td>
</tr>
<tr>
<td></td>
<td>RF</td>
<td>0.37</td>
<td>0.12</td>
</tr>
<tr>
<td>Min C</td>
<td>MLR***</td>
<td>0.28</td>
<td>71.39</td>
</tr>
<tr>
<td></td>
<td>RF</td>
<td>0.31</td>
<td>77.16</td>
</tr>
<tr>
<td>Mg</td>
<td>MLR**</td>
<td>0.15</td>
<td>110.55</td>
</tr>
<tr>
<td></td>
<td>RF</td>
<td>0.34</td>
<td>108.43</td>
</tr>
<tr>
<td>K</td>
<td>MLR</td>
<td>0.16</td>
<td>0.35</td>
</tr>
<tr>
<td></td>
<td>RF</td>
<td>0.28</td>
<td>117.72</td>
</tr>
<tr>
<td>Na</td>
<td>MLR***</td>
<td>0.37</td>
<td>13.12</td>
</tr>
<tr>
<td></td>
<td>RF</td>
<td>0.38</td>
<td>15.50</td>
</tr>
<tr>
<td>Ca</td>
<td>MLR**</td>
<td>0.3</td>
<td>0.12</td>
</tr>
<tr>
<td></td>
<td>RF</td>
<td>0.34</td>
<td>1019.05</td>
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<tr>
<td>pH</td>
<td>MLR***</td>
<td>0.4</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td>RF</td>
<td>0.21</td>
<td>0.70</td>
</tr>
<tr>
<td>Oxalate Extractable Fe</td>
<td>MLR***</td>
<td>0.25</td>
<td>0.29</td>
</tr>
<tr>
<td></td>
<td>RF</td>
<td>0.21</td>
<td>14.79</td>
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<tr>
<td>Oxalate Extractable Al</td>
<td>MLR**</td>
<td>0.18</td>
<td>0.43</td>
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<tr>
<td></td>
<td>RF</td>
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<td>17.47</td>
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<td>Oxalate Extractable P</td>
<td>MLR***</td>
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<td>0.47</td>
</tr>
<tr>
<td></td>
<td>RF</td>
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<td>5.06</td>
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<td>Nitrification</td>
<td>MLR***</td>
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<td>0.0031</td>
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<td></td>
<td>RF</td>
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<td>0.0036</td>
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<tr>
<td>Mineralization</td>
<td>MLR***</td>
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<td>0.0871</td>
</tr>
<tr>
<td></td>
<td>RF</td>
<td>0.29</td>
<td>0.0953</td>
</tr>
<tr>
<td>7-day Net Nitrification</td>
<td>MLR**</td>
<td>0.24</td>
<td>0.0022</td>
</tr>
<tr>
<td></td>
<td>RF</td>
<td>0.29</td>
<td>0.0953</td>
</tr>
<tr>
<td>7-day Net Mineralization</td>
<td>MLR*</td>
<td>0.15</td>
<td>0.0068</td>
</tr>
<tr>
<td></td>
<td>RF</td>
<td>0.23</td>
<td>0.0026</td>
</tr>
</tbody>
</table>

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$
4.2 Total Soil Carbon (C_{total}) and Nitrogen (N_{total}), and Mineralizable Carbon:

Table 3: β coefficients of C_{total}, N_{total} and Mineralizable Carbon from MLR models

<table>
<thead>
<tr>
<th>Variables</th>
<th>C β coefficients</th>
<th>N β coefficients</th>
<th>Min C β coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily Precipitation</td>
<td>-0.44 ***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean Temperature</td>
<td>0.27 *</td>
<td>-0.01</td>
<td>39.09</td>
</tr>
<tr>
<td>Pre-Fire NDVI</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NDWI</td>
<td>-0.07</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pre-Fire EVI</td>
<td>0.21 **</td>
<td>0.05 *</td>
<td></td>
</tr>
<tr>
<td>Post-Fire EVI</td>
<td>0.08</td>
<td>0.08 ***</td>
<td>-30.67</td>
</tr>
<tr>
<td>dNBR</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BAI</td>
<td>-0.04</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Flow Direction</td>
<td>0.15 *</td>
<td></td>
<td>35.30 *</td>
</tr>
<tr>
<td>Elevation</td>
<td></td>
<td>-0.05</td>
<td></td>
</tr>
<tr>
<td>Aspect</td>
<td>0.24 **</td>
<td>0.086 **</td>
<td>45.70 *</td>
</tr>
<tr>
<td>TPI</td>
<td>0.07</td>
<td></td>
<td></td>
</tr>
<tr>
<td>McNab Curvature</td>
<td>-0.26 *</td>
<td>-0.07</td>
<td>-69.91 **</td>
</tr>
<tr>
<td>Roughness</td>
<td>0.07</td>
<td>-0.01</td>
<td></td>
</tr>
<tr>
<td>Flow Accumulation</td>
<td></td>
<td>0.05</td>
<td></td>
</tr>
<tr>
<td>Slope</td>
<td></td>
<td></td>
<td>-3.78</td>
</tr>
</tbody>
</table>

All environmental predictors mean-centered and scaled by one standard deviation. *** p < 0.001; ** p < 0.01; * p < 0.05

The MLR model outperformed the RF model with respect to both R^2 and RMSE for C_{total} (Table 6). **Fire variables were not** significant predictor variables in the MLR model. The MLR model of C_{total} (p<0.00001, adj R^2=0.37, RMSE=0.34, Table 7), included daily precipitation (<0.001), aspect (<0.01), post-fire EVI (<0.01), flow direction (<0.01), McNab Curvature (<0.01) and mean temperature (<0.05) as significant explanatory variables (Table 6, Table 7). The non-linear, non-parametric RF model for C_{total} (R^2=0.32, RMSE=1.84, Table 6) provided different results than the MLR model (Figure 3) with **fire variables being present** in the model. Elevation and daily precipitation were the variables of highest importance, respectively. Importance in an RF model indicates how much the much the variable affects the accuracy of the model, with higher importance values having a higher effect on the
accuracy of the model. The dNBR and clay index were included in the RF model but not in the MLR model while daily precipitation and post-fire EVI were included in both models.

The MLR model for total N (N\textsubscript{total}) (Adj R\textsuperscript{2}=0.29, RMSE=0.12 p<0.001, Table 6) and the RF model for N\textsubscript{total} (R\textsuperscript{2}=0.37, RMSE=0.12, Table 6) included fire covariates. The dNBR (<0.001), aspect (<0.01), and post-fire EVI (<0.05) were significant explanatory variables in the MLR model (Table 7). Like C\textsubscript{total}, N\textsubscript{total} was significant and positively correlated with post-fire EVI (Table 7). In contrast to C\textsubscript{total}, which was positively correlated but not significant, dNBR was significantly positively correlated to N\textsubscript{total}, suggesting that as burn severity increases, so does N\textsubscript{total} (Table 7). The RF model for N\textsubscript{total} outperformed the MLR model (Table 7, Figure 3). Daily precipitation and elevation were the two most important variables for the N\textsubscript{total} RF model, while neither were significant in the MLR model (Table 7, Figure 3). However, dNBR was an important variable in both models.

The MLR model was significant for mineralizable C (Min C, p-value <0.001, Adj R\textsuperscript{2}=0.28, RMSE=71.39, Table 6), and unlike the RF model for Min C (Figure 7), did not include fire variables. Like C\textsubscript{total}, Min C was significantly negatively correlated with both McNab curvature and daily precipitation while being significantly positively correlated with flow direction (Table 7). Min C, C\textsubscript{total} and N\textsubscript{total} MLR models were all significantly positively correlated with aspect. The Min C RF model (R\textsuperscript{2}=0.31, RMSE=77.16, Table 6) had a higher R\textsuperscript{2} value than the MLR indicating a higher explanatory power than the MLR model, but the MLR also had a lower RMSE indicating a better model fit (Table 6). The variables of importance for
the Min C model were roughness, elevation, TRI, daily precipitation, slope and 
**RdNBR** (Figure 3). Only daily precipitation, slope and McNab curvature were 
variables that had crossover between both models.
Figure 3: Heatmap of Total C, Total N and Mineralizable Carbon displaying variable importance for covariates from RF models
4.3 Soil Cations and pH:

Table 4: β coefficients of extractable cations from MLR models

<table>
<thead>
<tr>
<th>Variables</th>
<th>$Na_{ex} \beta$ coefficients</th>
<th>$Mg_{ex} \beta$ coefficients</th>
<th>$Ca_{ex} \beta$ coefficients</th>
<th>$pH \beta$ coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily Precipitation</td>
<td>-20.80 ***</td>
<td>-74.69 **</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean Temperature</td>
<td>12.57 **</td>
<td>44.95 *</td>
<td>-0.01</td>
<td>-0.039 *</td>
</tr>
<tr>
<td>Pre-Fire NDVI</td>
<td></td>
<td>20.95</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NDWI</td>
<td>3.45</td>
<td></td>
<td>-0.04 *</td>
<td></td>
</tr>
<tr>
<td>Pre-Fire EVI</td>
<td>5.58</td>
<td></td>
<td>0.06 *</td>
<td></td>
</tr>
<tr>
<td>Post-Fire EVI</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>July EVI</td>
<td>-3.30</td>
<td></td>
<td>-0.02</td>
<td></td>
</tr>
<tr>
<td>dNBR</td>
<td></td>
<td>0.09 ***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NBRT</td>
<td></td>
<td></td>
<td>0.08 ***</td>
<td></td>
</tr>
<tr>
<td>RdNBR</td>
<td>1.20</td>
<td></td>
<td>-0.04</td>
<td>-0.02</td>
</tr>
<tr>
<td>BAI</td>
<td></td>
<td></td>
<td>0.05 *</td>
<td></td>
</tr>
<tr>
<td>Flow Direction</td>
<td></td>
<td></td>
<td>-0.01</td>
<td>0.02</td>
</tr>
<tr>
<td>TRI</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elevation</td>
<td></td>
<td></td>
<td>-0.05</td>
<td></td>
</tr>
<tr>
<td>Aspect</td>
<td>3.15</td>
<td>41.73 *</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TPI</td>
<td>4.24 *</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>McNab Curvature</td>
<td></td>
<td>-65.60 **</td>
<td>-0.07</td>
<td>-0.04</td>
</tr>
<tr>
<td>Roughness</td>
<td>0.27</td>
<td>-1.018</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Flow Accumulation</td>
<td></td>
<td></td>
<td>-0.03 *</td>
<td></td>
</tr>
<tr>
<td>Clay Index</td>
<td>3.61</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

All environmental predictors mean-centered and scaled by one standard deviation. *** p < 0.001; ** p < 0.01; * p < 0.05

The MLR model for $Na_{ex}$ (p-value <0.0001, Adj $R^2=0.37$, RMSE=13.12, Table 8) had comparable results to the RF model ($R^2=0.38$, RMSE=15.5, Table 6) with the exception of the RF model including fire covariates. Mean temperature (<0.01) was significantly positively correlated to $Na_{ex}$ (Table 3). TPI (<0.05) and daily precipitation (<0.001) were significantly positively and negatively correlated to $Na_{ex}$ respectively (Table 3). Like the MLR model (p <0.001) for $Na_{ex}$, the RF model for $Na_{ex}$ had daily precipitation as the most important variable (Table 8, Figure 4).
Aspect, **NBRT**, and elevation were important variables for the RF model but did not show up in the MLR model for Na\textsubscript{ex} (Table 8, Figure 4).

A MLR model for Mg\textsubscript{ex} (p-value <0.01, Adj \(R^2=0.15\), RMSE=110.55, Table 6) was outperformed by an RF model (R\(^2=0.34\), RMSE=108.43, Table 6). The MLR model **did not include significant fire covariates, while the RF model did**. The most significant variables for the MLR model were daily precipitation (p<0.01) and McNab Curvature (p<0.01) which were significantly negatively correlated to Mg\textsubscript{ex}. Aspect (p<0.05), and mean temperature (p<0.05) were significantly positively associated with Mg\textsubscript{ex} (Table 8). Daily precipitation was the only variable of significance in the RF model that also appeared in the MLR model (p-value <0.01, Table 5, Figure 4). Roughness was important in the RF model but was not of significance in the MLR model. TPI, flow accumulation, prefire EVI, mean temperature and dNBR were also variables of importance in the RF model (Figure 4).

The MLR model for Ca\textsubscript{ex} (p <0.001, Adj \(R^2=0.30\), RMSE=873.03, Table 6) outperformed the RF model (R\(^2=0.34\), RMSE=1019.05, Table 6) due to a lower RMSE and **both models included fire variables** (Table 8, Figure 4). Unlike other soil cations, dNBR (<0.001), flow accumulation (<0.05), post-fire EVI (<0.05) and flow direction (<0.05) were significantly positively correlated with Ca\textsubscript{ex} (Figure 4). NDWI, elevation, **NBRT** and RdNBR are the highest variables of significance in RF model of Ca\textsubscript{ex} and with only dNBR appearing in both models, albeit as a much lower variable of significance in the RF model (Table 8, Figure 4).

The MLR model for soil pH (p-value <0.0001, Adj \(R^2=0.40\), RMSE=0.09, Table 6) outperformed the RF model (R\(^2=0.21\), RMSE=0.70, Table 6) with a higher R\(^2\) and
lower RMSE. The **NBRT** (<0.001) and NDWI (<0.05) were significantly positively correlated to pH, while Pre-fire NDVI (<0.05) and mean temperature (<0.05) were significantly negatively correlated to pH (Table 8). The RF model provided multiple fire variables with **RdNBR**, **NBRT** and **BAI** (Figure 4) being of high importance. In both the MLR and RF pH model **NBRT** appeared as a significant variable.
Figure 4: Heatmap of cations displaying variable importance for covariates from RF models
### 4.4 Oxalate Extractable Fe, Al and P:

Table 5: β coefficients of oxalate extractable Fe, Al and P from MLR models

<table>
<thead>
<tr>
<th>Variables</th>
<th>Fe₀ β coefficients</th>
<th>Al₀ β coefficients</th>
<th>Po β coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily</td>
<td>0.06</td>
<td>-0.37 *</td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.22 **</td>
<td>0.48 **</td>
<td></td>
</tr>
<tr>
<td>NDWI</td>
<td>0.26 ***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post-Fire EVI</td>
<td>-0.12</td>
<td>0.10</td>
<td></td>
</tr>
<tr>
<td>July EVI</td>
<td>-0.09</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pre-fire NDVI</td>
<td>-0.34 **</td>
<td>-0.36 *</td>
<td></td>
</tr>
<tr>
<td>July NDVI</td>
<td>0.02</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BAI</td>
<td>-0.10</td>
<td>-0.13</td>
<td>-0.25 **</td>
</tr>
<tr>
<td>dNBR</td>
<td>0.06</td>
<td>0.06</td>
<td>0.39 *</td>
</tr>
<tr>
<td>NBRT</td>
<td>-0.08</td>
<td>0.11</td>
<td>0.47 **</td>
</tr>
<tr>
<td>RdNBR</td>
<td></td>
<td>-0.03</td>
<td></td>
</tr>
<tr>
<td>Flow</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TRI</td>
<td>-0.02</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Soil Carbonates</td>
<td>0.06</td>
<td>0.07</td>
<td>0.02</td>
</tr>
<tr>
<td>Clay Index</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

All environmental predictors mean-centered and scaled by one standard deviation. *** p < 0.001; ** p < 0.01; * p < 0.05

The MLR model for Fe₀ (p-value <0.001, Adj R²=0.25, RMSE=0.29, Table 6) outperformed the RF model but did not include any fire variables (R²=0.21, RMSE=14.79, Table 6). The only significant variable for the MLR model of Fe₀ was NDWI (<0.001) which was significantly positively correlated (Table 9). In the RF model for Fe₀, fire variables were of importance with dNBR (Figure 5) being present. Pre-fire and post-fire NDVI’s, mean temperature and NDWI were important variables in the RF model as well (Figure 5), which had many dissimilarities from the MLR model (p-value <0.001).

Like Fe₀ the MLR model for Al₀ (p-value <0.01, Adj R²=0.08, RMSE=0.43, Table 6) outperformed the RF model (R²=0.25, RMSE=17.47, Table 6) and the MLR
model did not include any fire variables while the RF model did (Table 9, Figure 5). Unlike Fe₀ the significant variables in MLR model for Al₀ were mean temperature (<0.01), and fire NDVI (<0.01) which were negatively and positively correlated, respectfully (Table 9). The RF for Al₀ provided different results than the MLR model (p-value <0.01, Table 9, Figure 5). The most important variables were daily precipitation, mean temperature, elevation, prefire and post-fire NDVI’s and dNBR, respectively. The only variables of significance that affected both models were mean temperature and post-fire NDVI.

Similar to both Fe₀ and Al₀, the MLR model for P₀ (p-value <0.001, Adj R²=0.30, RMSE=0.47, Table 6) outperformed the RF model (R²=0.24, RMSE=5.06, Table 6), however both models heavily included fire covariates. Mean temperature was significantly positively correlated for P₀, Fe₀ and Al₀. RdNBR (<0.01), NBRT (<0.05), and dNBR (<0.05) are all significantly positively associated to P₀ (Table 9). BAI (<0.01), daily precipitation (<0.05) and post-fire NDVI (<0.05) were significantly negatively associated to P₀ (Table 9). There was crossover between the MLR and RF models for P₀ with RdNBR, dNBR, NBRT and mean temperature (Table 9, Figure 5). For all three elements in the oxalate extraction, variable importance from RF were similar with all models having prefire and post-fire NDVI, dNBR, and July EVI as important variables (Figures 5).
Figure 5: Heatmap of Oxalate extractable Fe, Al and P displaying variable importance for covariates from RF models
4.5 Nitrification and Mineralization:

Table 6: $\beta$ coefficients of extractable cations from MLR models

<table>
<thead>
<tr>
<th>Variables</th>
<th>$NO_3^{-}$ $\beta$ coefficients</th>
<th>$NH_4^+$ $\beta$ coefficients</th>
<th>7-day nitrification $\beta$ coefficients</th>
<th>7-day mineralization $\beta$ coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily Precipitation</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean Temperature</td>
<td>-0.003**</td>
<td>0.003***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Prefire NDVI</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Prefire EVI</td>
<td>0.02</td>
<td>-0.001</td>
<td>0.003**</td>
<td></td>
</tr>
<tr>
<td>Post-Fire EVI</td>
<td>-0.001</td>
<td>0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Slope</td>
<td>-0.051***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>dNBR</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NBRT</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RdNBR</td>
<td>0.001*</td>
<td>-0.002*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BAI</td>
<td>0.002**</td>
<td>-0.001</td>
<td>-0.003*</td>
<td></td>
</tr>
<tr>
<td>Flow Direction</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TRI</td>
<td>0.03**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elevation</td>
<td>0.001**</td>
<td>-0.001</td>
<td>-0.004</td>
<td></td>
</tr>
<tr>
<td>Aspect</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TPI</td>
<td>0.001**</td>
<td>-0.001</td>
<td>0.002*</td>
<td></td>
</tr>
<tr>
<td>McNab Curvature</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Roughness</td>
<td>-0.001</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Flow Accumulation</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Clay Index</td>
<td>0.002**</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

All environmental predictors mean-centered and scaled by one standard deviation.

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

A MLR model for initial $NO_3^-$ concentration (p-value <0.001, Adj $R^2=0.29$, RMSE=0.0031, Table 6) had similar results to the RF model ($R^2=0.30$, RMSE=0.0036, Table 6) and both models included fire covariates. Aspect (p<0.01), flow direction (p<0.01), clay index (p<0.01), and BAI (p<0.05) were significantly positively correlated, while prefire NDVI (<0.01) was significantly negatively correlated (Table 10). The non-linear, non-parametric RF model provided comparable results to the MLR model with covariate crossover of BAI, flow direction and aspect (Figure 6). The most important
variable was aspect, with BAI, RdNBR, NBRT, NDWI and flow direction also being variables of importance (Figure 6).

Like NO$_3^-$, the MLR model for initial NH$_4^+$ concentration (p-value <0.001, Adj $R^2$=0.24, RMSE=0.0871, Table 6) was outperformed by an RF model (R$^2$=0.29, RMSE=0.0953, Table 6) and both models were heavily influenced by fire variables. However, unlike NO$_3^-$, the variables of significance for the MLR model for initial NH$_4^+$ were NBRT (p<0.001), which had a negative correlation, and elevation (p<0.01), which had a positive correlation (Table 10). The RF model for NH$_4^+$ provided comparable results to the MLR model with NBRT, RdNBR and elevation being present in the RF model. NBRT and elevation were present in both models (Table 10, Figure 6).

A MLR model for 7-day net nitrification (p-value <0.01, Adj $R^2$=0.24, RMSE=0.0022, Table 6) was outperformed by the RF model (R$^2$=0.29, RMSE=0.0953, Table 6). The MLR model included fire covariates while the RF model did not (Table 10, Figure 6). The two most significant variables for the MLR model were daily precipitation (p<0.001), and prefire NDVI (p<0.001), which have a negative and positive correlation, respectively. The RdNBR (p<0.05) had a negative correlation with 7-day net nitrification while BAI (p<0.05) had a positive correlation (Table 10). The 7-day net nitrification RF model provided different results than the MLR model with the only covariate of significance that appeared in both models being daily precipitation. The primary variables of importance were elevation, with precipitation, flow direction, TRI and slope also being of importance (Figure 6).

As seen in both the initial NO$_3^-$ and NH$_4^+$ models, the model for 7-day net mineralization (p-value <0.05, Adj $R^2$=0.15, RMSE=0.0068, Table 6) was outperformed
by an RF model ($R^2=0.23$, RMSE=0.0026, Table 6). The RF model included fire covariates of importance while the MLR model did not. Significant and positively associated variables in the MLR model for 7-day net mineralization included post-fire EVI ($p<0.01$), McNab curvature ($p<0.05$), TPI ($p<0.05$), while flow direction ($p<0.05$) had a negative correlation (Table 10). The RF model for 7-day net mineralization provided comparable results to the 7-day net nitrification RF model with elevation, slope and TRI being variables of significance (Figure 6). However, TWI and BAI were also of high importance in the RF model.
Figure 6: Heatmap of nitrate, ammonium, nitrification and mineralization displaying variable importance for covariates from RF models
Here we explore the relationship between remotely sensed proxies for the soil forming factors, remotely sensed indicators of fire severity, and a suite of soil properties and soil health indicators, to understand the relative contribution of fire and select soil forming factors to the variability of soil properties in post-fire landscapes. Remotely sensed indicators such as RdNBR, dNBR, BAI and NBRT all significantly explained the variability of soil properties in the recently burned watershed. This suggests that the impact of fire on forest soil properties, as well as the short-term recovery of soil health, can be partially explained via remotely sensed indicators of fire severity. We demonstrate the relative contribution of remotely sensed proxies for soil development, along with remotely sensed indicators of fire, to explain the distribution of soil properties. We explore the relative contribution of fire to soil formation and add context to the discussion of fire as a potential soil forming factor (Certini, 2003). To the best of authors’ knowledge, there are few investigations that directly link remotely sensed indicators of fire severity (e.g., dNBR) to soil properties, and those that do typically correlate dNBR to soil hydrologic properties (Moody et al., 2016; Ebel et al., 2018). Furthermore, while multiple papers have correlated dNBR and vegetative burn severity (Cocke et al., 2005; Soverel et al., 2010; Hoscilo et al., 2013) none have combined remotely sensed variables that correlate to the soil forming factors with remotely sensed vegetation burn severity indicators, to better understand the spatial distribution of post-fire soil properties.

5.1 Soil Carbon:
Vegetation burn severity, measured with dNBR, was nonsignificant in the MLR model for total C, however it was an important variable in the RF model (Table 7, Figure
This may be due to the varying effects that fire intensity can have on soil C. High intensity fire has been found to decrease total C due to C combustion (Certini, 2003; Alexis et al., 2007; Alcañiz et al., 2018b; Adkins et al., 2019; Xu et al., 2022a). However, it has also been reported that low intensity fire may increase total soil C, and that the creation of pyrogenic C under anoxic burning conditions that occur in low intensity fire may increase total C (Maestrini et al., 2015; Alcañiz et al., 2016, 2018b; Pellegrini et al., 2021). Different forms of soil C may also vary differently with fire effects as found in Adkins et al. (2019) who indicate that mineral soil C does not change with fire severity, but total profile C does, due to combustion of surface litter (e.g. O horizon). Differential effects of fire on soil C may lead to non-linear relationships between measured vegetation burn severity and soil C (Pellegrini et al., 2021). Furthermore, there is a known disconnect between SBS and remotely sensed vegetation burn severity as vegetation burn severity reflects impacts to vegetation, which is often different than the thermal effects incurred in soil (Safford et al., 2007; Parsons et al., 2010; García-Llamas et al., 2019a; Saberi A,B et al., 2022; Fernández-Guisuraga et al., 2023a). This disconnect often leads to under or overpredictions of SBS as SBS is a combination of residence time and fire intensity and these have varying affects above and below ground (Safford et al., 2007; Parsons et al., 2010). Climate variables were an important indicator for total C in both the MLR and RF models (Table 7, Figure 3) due to climate variables having a dominant influence on soil carbon stocks (Carvalhais et al., 2014; Luo et al., 2017b), as it is known that both precipitation and temperature are drivers of soil carbon (Doetterl et al., 2015; Luo et al., 2017a). Topographic variables were also important in both the MLR and RF models (Table 7, Figure 3) due to the known correlation between topography, soil texture
and total C (Morris and Boerner, 1998). Terrain attributes have been demonstrated to be the dominant predictor of SOC within a DSM context with a correlation between the two (Grimm et al., 2008; John et al., 2022). Erosion has also been found to be a dominant cause of pyrogenic C movement due to its prevalence on the soil surface post-fire, highlighting another reason terrain variables may have been important (Abney and Berhe, 2018; Abney et al., 2019). EVI was prevalent in both the MLR and RF model due to EVI being sensitive to vegetation variations (Chen et al., 2011; Zheng et al., 2016).

Fire covariates were nonsignificant predictors of MinC for the MLR model (Table 7, Figure 3) and not a variable of importance in the RF model (Table X). This is contradictory to the work of Maslov et al. (2020) that found that moderate and high intensity fire affect mineralizable carbon. Similar to total C and N, climate and terrain variables (Table 7, Figure 3) affected both models for MinC, in agreement with other DSM reports (Scull et al., 2003; Lamichhane et al., 2019c; Xu et al., 2022b).

5.2 Extractable Cations and pH:

Fire covariates were minimal predictors for Mg ex and Na ex as the only fire variable in the RF model was NBRT and it was of low importance (Figure 4). With samples taken a full year post-fire, it is most likely that either an immediate post-fire increase, and then a return to prefire levels after a year due to leaching, or no change in Mg ex occurred (Scheun et al., 2004; Alcañiz et al., 2016; Thomaz, 2017). Na ex was likely mobilized during the vegetative burning process, and deposited in ash, which has been found to cause a minor increase in Na ex post-fire (Butler et al., 2020).

Climate and terrain covariates were dominant in models for Mg ex and Na ex (Table 8, Figure 4). Topography determines water flow throughout areas thus affecting the translocation of clay particles and in turn changing soil cation exchange capacity in
individual soils, especially in the steeply sloping California Coast Range terrain found in the studied watershed (Jenny, 1941; Brubaker et al., 1993; Khomo et al., 2011). The spatial distribution of \( \text{Mg}_{\text{ex}} \) and \( \text{Na}_{\text{ex}} \) is also affected by precipitation and temperature due to weathering and translocation of soil cations (Jenny, 1941; Povak et al., 2014; Shi et al., 2018). A negative correlation with precipitation indicates a reduction in both soil \( \text{Mg}_{\text{ex}} \) and \( \text{Na}_{\text{ex}} \) as precipitation increases, which is consistent with most literature (Hartikainen, 1978; Quilchano et al., 1995; Moslehi et al., 2019). Surprisingly, vegetation covariates did not appear as significant variables in any of the models for \( \text{Mg}_{\text{ex}} \) and \( \text{Na}_{\text{ex}} \) (Table 8), as has been reported elsewhere (Mazur et al., 2022). This may be due to wind and rain translocation of cations stored within ash before they could be integrated into the soil profile (Balfour et al., 2014).

Fire variables are presented as significant in both the MLR and RF models for \( \text{Ca}_{\text{ex}} \) (Table 8, Figure 4) indicating that fire plays a key role in \( \text{Ca}_{\text{ex}} \). In the MLR model there is a positive correlation with dNBR (Table 8), indicating that as vegetative burn intensity increases \( \text{Ca}_{\text{ex}} \) increases. This is corroborated by existing literature that indicates divalent cations increase post-fire (Lewis, 1974; Kennard and Gholz, 2001). However, it is unclear why the models for \( \text{Mg}_{\text{ex}} \) (a divalent cation, Table 8, Figure 4) did not include many fire covariates as current literature indicates that it follows similar patterns to \( \text{Ca}_{\text{ex}} \) post-fire. This could be due to \( \text{Mg}_{\text{ex}} \) being an order of magnitude lower in the soils sampled (Table 5) in this study (Kennard and Gholz, 2001; Cancelo-González et al., 2013). The increase in \( \text{Ca}_{\text{ex}} \) comes mostly from combustion of organic material and subsequent ash deposition and, to a lesser degree, from mineralization of organically bound cations (Kennard and Gholz, 2001; Bodí et al., 2014b). The NDWI, a vegetation
covariate is presented as the most important variable in the RF model for Ca$_{ex}$ (Figure 4) and post-fire EVI is of significance for the MLR model (Table 8), indicating vegetation has a large effect on Ca$_{ex}$ content in the soils of this study. This is unsurprising given vegetation’s role in predicting soil cations (Mahmoudabadi et al., 2017; Chagas et al., 2018).

Fire covariates also played a key role in both the MLR and RF models for soil pH (Table 8, Figure 4). This is supported by existing literature that reports an increase in pH post-fire due to the denaturation of organic acids and the resulting release of cations that are deposited into the soil through the ash (Kennard and Gholz, 2001; Certini, 2003; Notario del Pino et al., 2008; Alcañiz et al., 2018b; Xu et al., 2022a). In the MLR model (Table 8), NBRT was positively correlated with pH indicating that as the remotely sensed burn severity metric increases, pH increases, which agrees with Thomaz (2017), who found a positive linear trend between pH and burn intensity. Furthermore, RdNBR, NBRT and BAI were all variables of importance in the RF model (Figure 4) indicating fire plays an influential role in the variability of post-fire pH at the watershed scale. As expected, terrain and vegetation covariates were important in describing the variability of post-fire pH, due to pH’s tendencies to change with vegetation and topography (Brubaker et al., 1993), and the known correlation between these remotely sensed indices and pH (Iwashima et al., 2012; Xia et al., 2016).

5.3 Poorly Crystalline Fe, Al and Sorbed P: Vegetation burn severity (dNBR), is the most important variable in the RF model for Fe$_{O}$, unlike Al$_{O}$ (Table 9, Figure 5). This indicates that fire plays a key role in describing the distribution of poorly crystalline Fe in post-fire landscapes, in contradiction with reports that fire does not affect Fe$_{O}$ (Norouzi and Ramezanpour, 2013). However, it has
been found that fire does transform goethite into poorly crystalline hematite at relatively low temperatures of 300 °C (Koch et al., 2006; Lin et al., 2021). This would increase oxalate extractable Fe, as FeO is a measure of poorly crystalline Fe. Scullett-Dean et al. (2020) found an increase in poorly crystalline Fe with soil heating and cited the formation of dehydroxylated minerals as the reason for the increase in poorly crystalline Fe. Given the lack of consistency between MLR and RF models, we cannot reliably suggest that burn severity, as indicated by remotely sensed burn severity, is driving any changes to Fe-oxide crystallinity. However, NDWI was a significant predictor in MLR (Table 9), and in the top ten variables of importance in RF (Figure 5), suggesting that this remotely sensed indicator of plant water status has some explanatory power of FeO. This may be due to the relationship between soil redox conditions, plant water status, and Fe-crystallinity, but these connections are speculative, and outside the scope of this study (Munch et al., 1978; Gao, 1996b; Wang et al., 2008).

Similar to FeO, the dehydroxylation of minerals during intense fire most likely affects AlO as well (Yusiharni and Gilkes, 2012; Scullett-Dean et al., 2020). However minimal fire variables were found within the models (Table 9, Figure 5) with none of significance showing in the MLR but appeared as variables of importance showing in the RF model. Due to the controversy between the models, we cannot state that fire significantly impacts AlO, however the RF model does suggest that fire may impact AlO.

Fire significantly impacted oxalate extractable P (Po). For the MLR model (Table 9) there were significant positive associations between Po and NBRT, RdNBR, and dNBR, indicating as vegetative burn severity increases, Po increases. This does not align with Alcañiz et al. (2018), or Durán et al. (2008) that both indicate an immediate post-fire
increase in available soil P and a resulting decrease in available soil P one-year post-fire. However, our results provide a potential explanation for the decline in available P reported elsewhere. We report that sorbed P (P\textsubscript{o} is P released from the reduction of poorly crystalline Fe/Al-oxides) increases with burn severity and remains elevated one-year post-fire. Our data suggest that the initial post-fire pulse of available P from pyromineralization of organic matter and leaf litter may in part be retained and bound to Fe/Al-oxides. Sorbed P can contribute to eutrophication through transport on colloids and subsequent release to the water column via Fe-reduction, releasing bound P (Łukawska-Matuszewska et al., 2013; Bodí et al., 2014a). This highlights a potential new and more persistent loss pathway of P to aquatic systems in post-fire landscapes (Scullett-Dean et al., 2020). However, additional work is required to further disentangle potential fire-induced changes to P biogeochemistry in forested post-fire landscapes.

5.4 Nitrogen Dynamics:
Vegetation burn severity (dNBR) was significantly positively associated with total N in MLR (Table 7, Figure 3), and a top predictor in RF indicating an increase in total N with an increase in remotely sensed burn severity. This is contradictory to Kennard and Gholz (2001) who reported an increase in N post-fire, but a decrease after 8 months in a tropical dry forest while Adkins et al. (2019) found no variation in total N with fire severity. Alcañiz et al. (2018) found an increase in N post-fire due to a low thermal pulse going through the soil, causing insignificant damage to N pools and the resulting incorporation of ash into the soils. Furthermore, it has been reported that total soil N increases post-fire due to ash rich in N being incorporated into the soil and increased mineralization rates post-fire (Agbeshie et al., 2022). The literature for post-fire effects on total N is contradictory with studies showing both increases and decreases in total N
one-year post-fire (Agbeshie et al., 2022). Here, we speculate that the correlation between soil N and dNBR may be due to the incorporation of N rich ash into the soil, however we did not observe a correlation between fire variables and mineralization rates (Chafer et al., 2016; Sánchez-García et al., 2023). Similar to soil C, climate and topographic variables affected both the MLR and RF models (Table 7, Figure 3) due to the effects on soil texture and N cycling climate and topography have (Jenny, 1941; Morris and Boerner, 1998; Carvalhais et al., 2014). NDVI is of high importance in the RF model (Figure 3) in agreement with other reports of vegetation covariates as important explanatory variables in the spatial distribution total N (Mahmoudabadi et al., 2017; Hossen et al., 2021; Xu et al., 2022b).

For nitrate, the MLR and RF models (Table 10, Figure 6) had major differences pertaining to fire variables. Only BAI was significant in the MLR model, with a positive correlation with nitrate indicating that as the charcoal signature increases, nitrates increase. The RF model also included BAI as a variable of importance for the prediction of nitrates, but unlike the MLR model, the RF model included RdNBR and NBRT indicating that these fire variables have a strong non-linear relationship with the soil nitrates in this study. Typically, there is an increase in nitrates post-fire due to ash deposits, increased nitrification, pyrolysis of organic materials, or decreased uptake by plants and microbes (Wan et al., 2001; Adkins et al., 2019; Agbeshie et al., 2022). Soil nitrates are also relatively mobile and can be leached post-fire which may cause a decrease in nitrates (Su et al., 2022).

Unlike the nitrate models, NBRT was included in both the MLR and RF ammonium models (Table 10, Figure 6) as the singular fire variable. It was the highest
variable of importance in the RF model and of high significance in the MLR model, with a strong negative linear correlation between ammonium and NBRT indicating as remotely sensed burn severity is increased, ammonium decreases. This is contradictory to some current findings that illustrate an increase in ammonium 6 months post-fire all the way to a 6-fold increase in nitrates three years post-fire (Wan et al., 2001; Adkins et al., 2019; Kucuk and Kahveci, 2020). This post-fire decrease in ammonium may be due to reduced C inputs as a higher burn intensity leads to increased C volatilization (Smithwick et al., 2005). Koyama et al. (2012) found that ammonification is drastically reduced post-fire and as these samples are taken a full year post-fire, reduced ammonification may be another explanation for the presence of fire variables within the ammonium models, however, we found no strong relationship between net-mineralization and fire covariates. Increased nitrification post-fire was another considered option for the reduction in post-fire ammonium as Ball et al. (2010a) found a post-fire increase in nitrification. However, results from this study indicate a reduction in nitrification with increasing burn intensity so this theory was discarded.

There is a large disparity between the MLR and the RF models for 7-day net nitrification (Table 10, Figure 6) pertaining to fire variables. For the MLR model, a negative correlation with RdNBR and positive correlation with BAI indicate a decrease in nitrification rates with burn intensity and an increase with charcoal content, while the RF model includes no fire variables. This increase in nitrification rates with increased charcoal aligns with current literature that indicates that charcoal increases nitrification (Ball et al., 2010b). The decrease in nitrification rates with higher remotely sensed burn intensity is most likely due to nitrifying organisms being affected by the resulting thermal
impulse in the soil (Gómez-Rey and Gonzalez-Prieto, 2013). Ibáñez et al. (2022) found a decrease in nitrification post-fire, however, this is contrary to Ball et al. (2010), who found that nitrification rates increase post-fire. The contrast may be due to nitrification rates varying as these rates depend upon vegetation type, plant recovery and the incurred nutrient uptake, and climatic and topographic conditions (Stephens and Homyak, 2023). The varying nitrification rates may be affected by how N-rich the ash deposits remaining in the soil are, which is most likely why topographic and climatic variables are of high importance in both models.

Unlike the 7-day nitrification models, fire variables (BAI) were of importance in the 7-day net N mineralization RF model (Figure 6), and the MLR model (Table 10) provided no fire variables of significance. With only one fire variable appearing in both models, the minimal impact of fire variables indicates that environmental covariates are more important than fire variables in the role of inference and prediction of net mineralization. This aligns with existing literature that indicates changes in nitrification rates and environmental factors such as topography and precipitation (Stewart et al., 2014; Grzyb et al., 2020). This is contrary to Gómez-Rey and Gonzalez-Prieto (2013) who found a significant increase in post-fire mineralization due to the increase in partially burned vegetation being added to the soil and resulting enhancement of microbial activity. The lack of fire variables in the mineralization models may be due to the soils being N limited, leading to reduced mineralization rates overall, or mineralization rates may have had an immediate increase post-fire, and then decrease with time (Wang et al., 2012b).
5.5 Limitations:
There are many limitations within this study that may have created unforeseen impacts on the results. One of the largest limitations was sample timing, with samples being taken a full year post-fire. This allows for ash movement on the soil surface that has the potential to change where nutrient dense ash is deposited, in turn affecting the spatial variability of post-fire soil nutrients (Bodí et al., 2014a; Lewis et al., 2021). An option to mitigate this would be to take remotely sensed data closer to the time of the sampling as opposed to strictly pre and post-fire. This may allow for an increased understanding of soil and vegetation regeneration post-fire (Dos Santos et al., 2020). We also believe that increasing sample size would have a large impact on our modeling as it has been found that the optimal sample density for DSM style modeling that utilizes Conditional Latin Hypercube sampling is 10.06 samples/km² (Yang et al., 2020). Higher resolution satellite imagery may have increased model accuracy as well; however, this is expensive and creates a necessity for higher processing power than was available during this study. If possible, imagery taken during the fire could be utilized as well to capture residence time and intensity of the fire. However, this is difficult because one would need a satellite positioned over the fire for the entirety of the fire with a high temporal resolution. Another option to remotely sense vegetative burn severity would be to utilize drone-based LiDAR to create pre and post-fire fuel models (Andersen et al., 2004; Li et al., 2022). The difference between the pre and post-fire models may increase our understanding of the fires’ effects on the surrounding ecosystem. Overall, this study has many limitations as we are trying to model soil nutrients (extremely heterogeneous at the watershed scale) from space, however this study is a large step towards understanding spatial post-fire nutrient variability and their correlations to remotely sensed indices.
Chapter 6

CONCLUSION

Soils are the great ecological integrator and when thermally altered, particularly with high-intensity fire, may significantly compromise post-fire ecosystems. The incineration of large quantities of biomass, leads to ecological impacts such as increased atmospheric greenhouse gasses, reduced water filtration, reduced soil quality and increased soil erosion, air pollution, nutrient pulses and water runoff (Chen, 2006; Gajendiran et al., 2024). Soil health is altered with severe and lasting biogeochemical effects such as reduced soil C and N or increased soil pH (Certini, 2003). However, both fire and soils are spatial heterogenous. To better understand the spatial effects of fire on soil we created a DSM model and included remotely sensed covariates that correspond to vegetation burn severity. This was done by deploying a raster-stack of environmental covariates, rasters for fire severity (dNBR, RdNBR, BAI and NBRT), analyzing field soil samples for soil health and mineralogical indicators and then utilizing multi-linear regression and random forest to ascertain the relative contribution of these remotely sensed fire severity covariates in explaining the spatial distribution of soil properties in post-fire watersheds. We report that remotely sensed indicators of fire severity help explain the spatial distribution of soil properties at the watershed scale. Including rasters of fire effects improved the description of target soil property variance, in concert with more traditional raster-based proxies for the soil forming factors. Thus, fire helps explain the spatial variability of soil properties in post-fire watersheds.

Our data indicates that remotely sensed fire severity variables significantly explained the variance of $N_{\text{total}}$, $Ca_{\text{ex}}$, pH, $P_O$, $NO_3^-$, $NH_4^+$, and 7-day Nitrification for MLR models. For the RF models, remotely sensed fire severity was found to be
important for \( C_{\text{total}} \), \( N_{\text{total}} \), Mineralizable Carbon, \( \text{Na}_{\text{ex}} \), \( \text{Mg}_{\text{ex}} \), \( \text{Ca}_{\text{ex}} \), pH, FeO, AlO, PO, NO\(_3^\cdot\), \( \text{NH}_4^+ \), and 7-day Mineralization. Soil properties that included remotely sensed fire severity variables as significant in both the MLR model and important in the RF model were \( N_{\text{total}} \), \( \text{Ca}_{\text{ex}} \), pH, PO, NO\(_3^\cdot\), and \( \text{NH}_4^+ \) indicating some confidence that these fire variables are spatially influenced by fire at the watershed scale. Furthermore, we report an increase in sorbed P (as measured via oxalate extractable P) with remotely sensed fire severity, suggesting a potentially unreported change to post-fire soil P dynamics, as well as a potential new loss pathway for P to waterways via erosion of sorbed P. This study has not only correlated remotely sensed burn severity to the above soil properties allowing us to better predict post-fire soil properties, but it has also found that fire influences the spatial variability of these post-fire properties at the watershed scale. With the addition of remotely sensed burn severity covariates, explained variance within our models increased. Mapping of post-fire soil properties was possible, but accuracy was low, leading to low reliability. The models most likely need higher sample density to explain enough variance to create useable maps. These models allow land managers to respond to post-fire soil thermal damage with increasing nuance, instead of strictly basing post-fire soil mitigation on SBS allowing them to be more time and cost effective in a world of increasing fire danger.
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APPENDICES

There are no significant variables for inferring the MLR relationship of soil K and the MLR model was not significant (Table 12). An RF model provided an $R^2$ of 0.28 with an RMSE of 117.72 (Figure 14). Fire variables did appear important with \textbf{RdNBR} and \textbf{dNBR} in the RF model.

![Variable Importance plot](image)

\textbf{Figure 7}: Variable Importance plot from random forest model relating environmental predictor variables to extractable potassium (ppm)
Twenty-eight-day net nitrification did not meet statistical assumptions for the MLR models. The RF model for 28-day net mineralization provided an $R^2$ of 0.23 and an RMSE of 0.1. Fire variables did appear important with RdNBR and BAI both appearing in the VIP graphs (Figure 14).
Figure 8: Variable Importance plot from random forest model relating environmental predictor variables to 21-day net nitrification (mg/kg/day)

Twenty-one-day net nitrification did not meet statistical assumptions for the MLR model. The RF model ($R^2 = 0.29$, RMSE = 0.0005) is included here and indicates some fire variables of high importance with RdNBR and BAI being highly important.
Figure 9: Variable Importance plot from random forest model relating environmental predictor variables to 21-day net mineralization (mg/kg/day)
VIP Plots for all Soil Properties Reported

Figure 10: Variable Importance plot from random forest model relating environmental predictor variables to total Carbon (%)
Figure 11: Variable Importance plot from random forest model relating environmental predictor variables to total Nitrogen (%)
Figure 12: Variable Importance plot from random forest model relating environmental predictor variables to mineralizable carbon (mg/kg/day CO₂)
Figure 13: Variable Importance plot from random forest model relating environmental predictor variables to extractable sodium (ppm)
Figure 14: Variable Importance plot from random forest model relating environmental predictor variables to extractable magnesium (ppm)
Figure 15: Variable Importance plot from random forest model relating environmental predictor variables to extractable calcium (ppm)
Figure 16: Variable Importance plot from random forest model relating environmental predictor variables to extractable pH
Figure 17: Variable Importance plot from random forest model relating environmental predictor variables to oxalate extractable iron (ppm)
Figure 18: Variable Importance plot from random forest model relating environmental predictor variables to oxalate extractable aluminum (ppm)
Figure 19: Variable Importance plot from random forest model relating environmental predictor variables to oxalate extractable phosphorus (ppm)
Figure 20: Variable Importance plot from random forest model relating environmental predictor variables to NO$_3^-$ (mg/kg)
Figure 21: Variable Importance plot from random forest model relating environmental predictor variables to NH4+ (mg/kg)
Figure 22: Variable Importance plot from random forest model relating environmental predictor variables to 7-day net nitrification (mg/kg/day)
Figure 23: Variable Importance plot from random forest model relating environmental predictor variables to 7-day net mineralization (mg/kg/day)