Research Note

CSIRO PUBLISHING

International Journal of Wildland Fire **2010**, *19*, 976–983

www.publish.csiro.au/journals/ijwf

Spectral analysis of charcoal on soils: implications for wildland fire severity mapping methods

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Abstract. Recent studies in the Western United States have supported climate scenarios that predict a higher occurrence of large and severe wildfires. Knowledge of the severity is important to infer long-term biogeochemical, ecological, and societal impacts, but understanding the sensitivity of any severity mapping method to variations in soil type and increasing charcoal (char) cover is essential before widespread adoption. Through repeated spectral analysis of increasing charcoal quantities on six representative soils, we found that addition of charcoal to each soil resulted in linear spectral mixing. We found that performance of the Normalised Burn Ratio was highly sensitive to soil type, whereas the Normalised Difference Vegetation Index was relatively insensitive. Our conclusions have potential implications for national programs that seek to monitor long-term trends in wildfire severity and underscore the need to collect accurate soils information when evaluating large-scale wildland fires.

Additional keywords: ash, char, combustion residue, remote sensing.

Introduction

Fire ecology studies (Viedma *et al.* 1997; Turner *et al.* 2003) and research investigating post-fire impacts on productivity in terrestrial ecosystems (Goetz *et al.* 2007) indicate that the severity of a fire can have important long-term biogeochemical consequences. Furthermore, recent studies evaluating long-term trends of wildland fires in the western United States (Morgan *et al.* 2008) have supported the predictions from the North America chapter of the 2007 Intergovernmental Panel on Climate Change (IPCC) that proposed, with very high confidence, an increased occurrence of higher-intensity wildfires in North America (Field *et al.* 2007). In particular, the occurrence of warmer and earlier springs coupled with periods of summer drought have recently been shown to be a significant driver of significant regional fire years (Heyerdahl *et al.* 2008; Morgan *et al.* 2008; Holden *et al.* 2010). Given that wildland fires are not only a major source of atmospheric gases and aerosols, but also impact numerous terrestrial processes such as soil biogeochemistry, surface hydrology and plant succession, among others (Crutzen and Andreae 1990; Turner *et al.* 2003; Lewis *et al.* 2008), the ability to generate accurate and consistent methods to map the extent and impact of these fires is essential. A major result of combustion in vegetation fires in the deposition of char onto the post-fire surfaces (Smith *et al.* 2005, 2007*a*; Roy *et al.* 2010), and therefore understanding the spectral mechanisms that different soil types exhibit with increasing depositions of charcoal onto these soil surfaces is critical for the development of effective and robust regional to national mapping and monitoring methods.

The majority of severity-mapping studies including national USA programs (e.g. Monitoring Trends in Burn Severity, MTBS) have focussed on applying a spectral index termed the Normalised Burn Ratio (NBR) or variants thereof (including multitemporal, thermal and relative versions). However, the wide-scale applicability and performance of this index remain uncertain given that contemporary studies have highlighted difficulties across different ecosystems (Roy *et al.* 2006; Hudak *et al.* 2007; Smith *et al.* 2007*a*; French *et al.* 2008; Lentile *et al.* 2009).

In general, two challenges persist with the widespread adoption of any spectral method to evaluate the long-term ecological impacts of remote and large-scale wildland fires. First, within an individual fire event, the perimeter frequently crosses different vegetation and soil types, which may not be known. Second, a considerable amount of post-fire severity assessment is done in a *post hoc ergo propter hoc* manner with limited prefire field validation data (i.e. because the effects followed the fire, the fire must have caused those effects) (van Wagtendonk *et al.* 2004; Cocke *et al.* 2005). A further challenge when developing spectral methods to remotely evaluate post-fire environments is the variability of likely reflectance values as a function of the intensity of the fire behaviour (Stronach and McNaughton 1989; Smith *et al.* 2005). Wildland fires are heterogeneous in nature, and even in fires characterised by large extents of crown-replacing forest fire, patches of relatively unburned vegetation can exist (Lentile *et al.* 2006, 2007). This heterogeneity is highly scale-dependent and typically increases at lower fire intensities with a higher probability of variable post-fire effects, from

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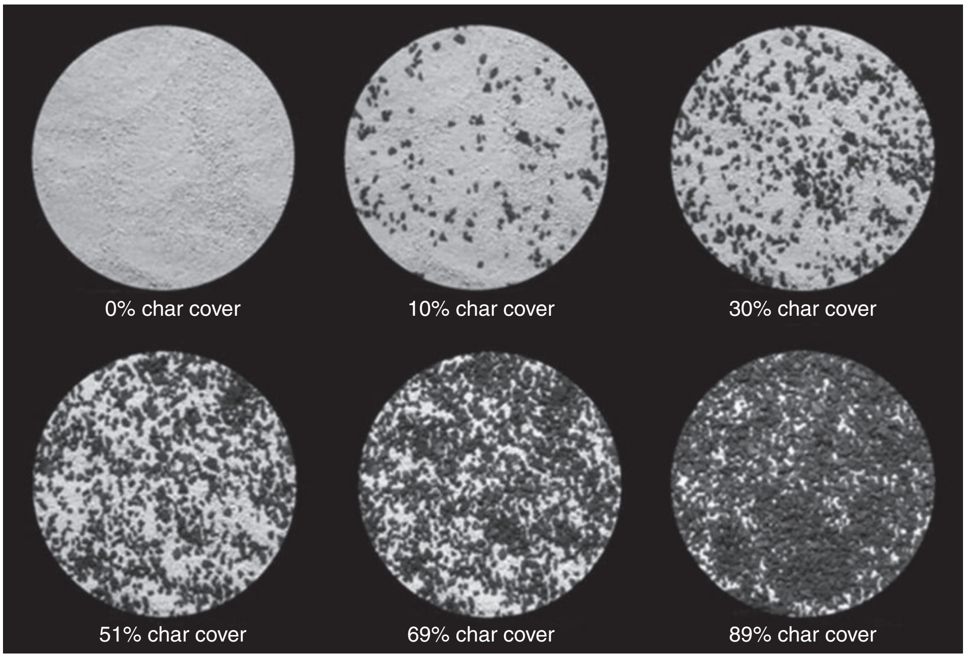

Fig. 1. Example of the experimental charcoal addition to the soil surfaces. Adjacent to the viewing circle, within the field of view of the digital camera, pure examples of each soil type and charcoal were situated to enable percentage cover calculation via a minimum distance supervised classification. For generality, the six soil–charcoal treatments were repeated four times under different orientations.

unburned organics to patches of complete combustion that can be observed within the scale of single Landsat pixels (Smith *et al.* 2005; Hudak *et al.* 2007). Variations in the fuel characteristics (loading, arrangement, moisture, etc.), topography, local meteorology, and thus the resultant fire behaviour can also result in considerable variation in the degree of fuel consumption at a site (Shea *et al.* 1996; Roy and Landmann 2005; Smith *et al.* 2005). Similarly, the sun-sensor geometry, often exacerbated owing to season and latitude, can lead to additional variations in surface reflectance (Verbyla *et al.* 2008; Veraverbeke *et al.* 2010).

As the spectral reflectance of charcoal is consistent at fixed particle sizes (Landmann 2003; Smith *et al.* 2005) and green vegetation spectral response curves are generally similar (Elvidge 1990), the former challenge could be minimised if the soil background was found to exhibit a minimal contribution to the post-fire spectral response. Given that prior studies investigating intimate mineral mixtures have observed that spectrally dark particles (termed opaques) added to spectrally bright mineral surfaces often result in a non-linear mixing scenario, where very small fractions of the opaque material dominate the combined spectrum (Nash and Conel 1974; Singer 1981; Clark 1983; Clark and Roush 1984), we would expect that a similar non-linear effect to also be observed when charcoal is deposited onto a soil background. If demonstrated, this would support the adoption of severity methods that require limited *a priori* information of the soil background (Hudak *et al.* 2007; Smith *et al.* 2007*a*). In the present Research Note, we investigate this phenomenon. Given recent studies have highlighted improved relationships over NBR type indices, when evaluating the post-fire charcoal coverage and numerous post-fire ecological effects (Hudak *et al.* 2007; Smith *et al.* 2007*a*; Lentile *et al.* 2009), we additionally assess the sensitivity of the NBR and other commonly applied spectral indices under increasing conditions of charcoal surface deposition to evaluate which spectral methods are potentially most appropriate for the large-scale monitoring of post-fire effects.

Methods

Charcoal was added incrementally to six different soils in a dark-room set up to test whether the combined spectral reflectance of different soils with increasing deposition of surface charcoal results in non-linear mixing (Figs 1, 2). The soils were oven-dried for 48 h at 50°C, ground to pass a 2-mm sieve, and characterised based on the US Soil Taxonomy (Soil Survey Staff 2006) and Munsell colour notation (Table 1). To minimise the variability of charcoal spectral reflectance due to particle size (Smith *et al.* 2005), standardised coconut charcoal with particle size between 1.68 and 3.35 mm (US mesh sizes 6–12) was used. The charcoal used was characterised by low spectral reflectance across the evaluated wavelengths (Fig. 2). This study did not focus on the deposition of white mineral ash, which occurs owing to the complete and near complete combustion of vegetation, as when it occurs it often does not occupy a large enough amount of a pixel's proportion to be detectable by moderate spatial resolution (~30-m pixel size) satellite sensors (Smith and Hudak 2005).

A circular soil tray, with adjacent pure endmember samples, was positioned below an 8-megapixel digital camera (Olympus America, Inc., Center Valley, PA) and an ASD FieldSpec Pro spectroradiometer fibre optic (Analytical Spectral Devices,

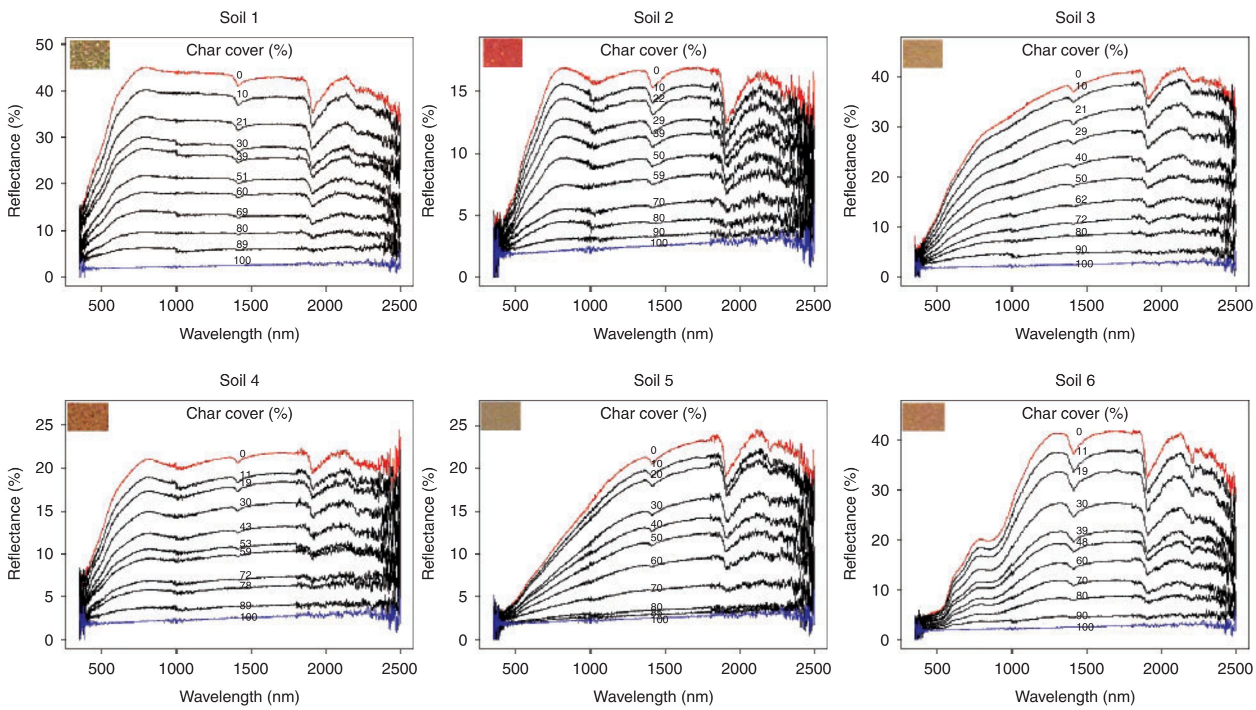

Fig. 2. The six soil spectra are presented with the increments of charcoal added. Spectral responses are presented on different scales to aid viewing.

Table 1. Subgroup, soil series, Munsell colour name and Munsell colour code (dry) of six soils used in this study

No.	Subgroup	Soil series	Colour name	Colour code
1	Typic Vitrixerands	–	Light grey	10YR 7/2
2	Typic Cryaquolls	Blackwell	Light brownish grey	10YR 6/2
3	Calcidic Haploxerolls	Ritzville	Yellowish brown	10YR 5/4
4	Xeric Haplocambids	Finley	Light brownish grey	10YR 6/2
5	Vitrandic Haploxerolls	Umatilla	Dark brown	10YR 3/3
6	Vitrandic Argixerolls	Klicker	Dusky red	10R 3/3

Table 2. Spectral indices used in this study computed using blue (B1), red (B3), near-infrared (B4), and shortwave infrared (B7) wavebands of Landsat-7 ETM+

Spectral index	Equation
Normalised Difference Vegetation Index	NDVI = (B4 − B3)/(B4 + B3)
Normalised Burn Ratio	NBR = (B4 − B7)/(B4 + B7)
Extended Vegetation Index	EVI = 2.5(B4 − B3)/(B4 + 6.0 × B3 − 7.5 × B1 + 1.0)
Optimised Soil Adjusted Vegetation Index	OSAVI = (B4 − B3)/(B4 + B3 + 0.16)

Boulder, CO) with a 25° of view, each positioned at nadir. The spectroradiometer consisted of two sensors; the first sensor was sensitive to wavelengths between 350 and 1050 nm and had a spectral resolution of 1.4 nm; the second sensor was sensitive to wavelengths between 1000 and 2500 nm and had a spectral resolution of 2 nm. The soil was illuminated with a full-spectrum 1000-W photography lamp, positioned as near to nadir as shadows would allow.

For generality, we selected six different soil samples that exhibited a range of spectral responses (Table 2, Fig. 2). To simulate a post-fire surface (in the absence of vegetation), charcoal was manually added evenly to each soil sample from 0 to 100% in approximate 5–10% intervals (Fig. 1). At each iteration, the spectral reflectance and a digital photograph were collected. The digital image was used to determine the percentage charcoal cover of the corresponding spectral measurement by conducting minimum-distance supervised classification on the digital image in the *Interactive Data Language* (IDL) software package (ITT Corporation, New York). Each spectral reflectance measurement represented an average of 20 distinct measurements. Prior to each soil run, a white Spectralon panel calibration measurement was made to enable calculation of reflectance. The addition of the charcoal to each of the six soils and the associated spectral and photography analysis were repeated four times. Following initial analysis of the spectral data, the experiment was repeated in full with new soil and charcoal samples; the same results were produced and are presented herein.

Data analysis

At each wavelength (for each soil), a linear regression model was fitted between observed (dependent variable) and predicted (independent variable) percentage charcoal cover (Piñeiro *et al.* 2008) in the open-source software package *R 2.8.1* (R Development Core Team 2009). The linearity of the fitted models was assessed based on the coefficient of simple determination (r^2). To understand the potential and widespread applicability of each spectral method, we investigated their sensitivity and performance to increases in charcoal cover on the different soils by converting the spectral reflectance measurements into the band-equivalent reflectance (BER: Trigg and Flasse 2000) of each Landsat-7 Enhanced Thematic Mapper (ETM+) sensor band. As highlighted in prior studies (Smith *et al.* 2005), the BER effectively simulates the band reflectance values that would be obtained if the satellite sensor was used *in situ* instead of the spectroradiometer. This approach convolves the band spectral response functions for each band of the Landsat sensor with the spectroradiometer data to calculate singular band reflectance values that can be used within the spectral indices. No actual Landsat data was used in this study. Although any satellite senor spectral response characteristics could be used, we chose Landsat given its recent widespread application in evaluating post-fire effects at landscape scales (e.g. MTBS project, Landfire).

Four representative indices were selected for analysis (Table 2): the Normalised Burn Ratio (Key and Benson 2006), developed for assessment of post-fire severity; Normalised Difference Vegetation Index (NDVI), previously used for post-fire vegetation recovery (Viedma *et al.* 1997); the Optimised Soil-Adjusted Vegetation Index (OSAVI), developed to better account for variations in the soil background (Rondeaux *et al.* 1996); and the Enhanced Vegetation Index (EVI: Huete *et al.* 2002) – developed as an improvement to NDVI for recent satellite sensors. The indices were selected solely based on their widespread use and by no means provide an exhaustive indication of which indices may be optimal for the remote assessment of post-fire effects. The relationship between percentage charcoal cover and spectral indices or Landsat-7 ETM+ bands was examined by fitting linear (and where appropriate non-linear) regression models. Goodness-of-fit was evaluated based on the coefficient of simple determination (r^2) (Fig. 3).

The relative equivalent noise (REN) statistic (Baret and Guyot 1991) was used to similarly evaluate the sensitivity of spectral indices to different levels of percentage charcoal cover and their resistance to soil background effects. Relatively lower REN numbers per index denote less noise and therefore high index sensitivity, although as calculated, this statistic does not account for variability in the gradient of the index–charcoal cover curve (Ji and Peters 2007). The relative equivalent percentage charcoal cover noise ($REN_{\%CC}$) was calculated as follows:

$$REN_{\%CC} = \frac{\sigma_R}{\%CC}\left(\frac{d(SI)}{d(\%CC)}\right)^{-1} \quad (1)$$

where σ_R is the standard deviation of the local regression of spectral index (*SI*) on percentage of charcoal cover (%*CC*); $\sigma_R/\%CC$ is a relative error term; and $d(SI)/d(\%CC)$ is the local slope of the *SI*–%*CC* relationship and expresses the sensitivity of the *SI* to change in %*CC*. Eight local slopes could be derived from eight 30%*CC* intervals (i.e. 0–30, 10–40, 20–50, 30–60, 40–70, 50–80, 60–90, and 70–100%*CC*). Thus, eight values of $REN_{\%CC}$ were computed for the %*CC* steps of 15, 25, 35, 45, 55, 65, 75, and 85% based on the eight local slopes.

Results

The addition of the charcoal to each of the soils resulted in a generally linear spectral mixing scenario (Fig. 2), with non-linearity only observed at the extremes of the spectroradiometer's wavelength ranges (i.e. <400 and >2400 nm), likely owing to standard sensor noise. Within the un-noisy wavelength region, the coefficient of determination for each soil's modelled *v.* measured spectral reflectance values with percentage charcoal cover remained >0.9, emphasising this linearity (data not shown).

The NBR index produces relationships with percentage charcoal cover that are highly dependent on soil type (Fig. 3), resulting in both positive and negative slopes depending on whether the near-infrared BER of the pure soil samples was greater or less than the BER of Landsat band 7. EVI produced equally poor relationships. In contrast, the NDVI and OSAVI relationships exhibit a range of different intercepts but the gradients are all negative (owing to the consistent magnitude difference between red and near-infrared BER values) with the root mean square errors on the order of 4–10%, compared with 8–29% for NBR and 22–33% for EVI. These results further show that for the six selected soils, the threshold for detection of the soil absorption features is approximately at 60% charcoal cover, which, given the results of prior studies, is typically what is achieved in the majority of fire-affected pixels (e.g. Smith *et al.* 2007*b*). This implies that the post-fire assessment of specific soils by the absorption features may prove difficult, making *a priori* evaluation of soil type a priority.

Among the studied indices, NDVI and OSAVI are most sensitive to variation in percentage charcoal cover and most resistant to soil background effects as indicated by the lowest $REN_{\%CC}$ values (Fig. 4). The sensitivity of NDVI to variation in percentage charcoal cover and its resistance to variation in soil background effects increases up to a charcoal cover of ~45% and stays fairly consistent thereafter. The NDVI index exhibits a high sensitivity across the entire range of percentage charcoal cover.

Discussion and conclusions

Although the linear mixing result generally supports prior fire studies (Landmann 2003; Smith *et al.* 2005), it is contrary to the

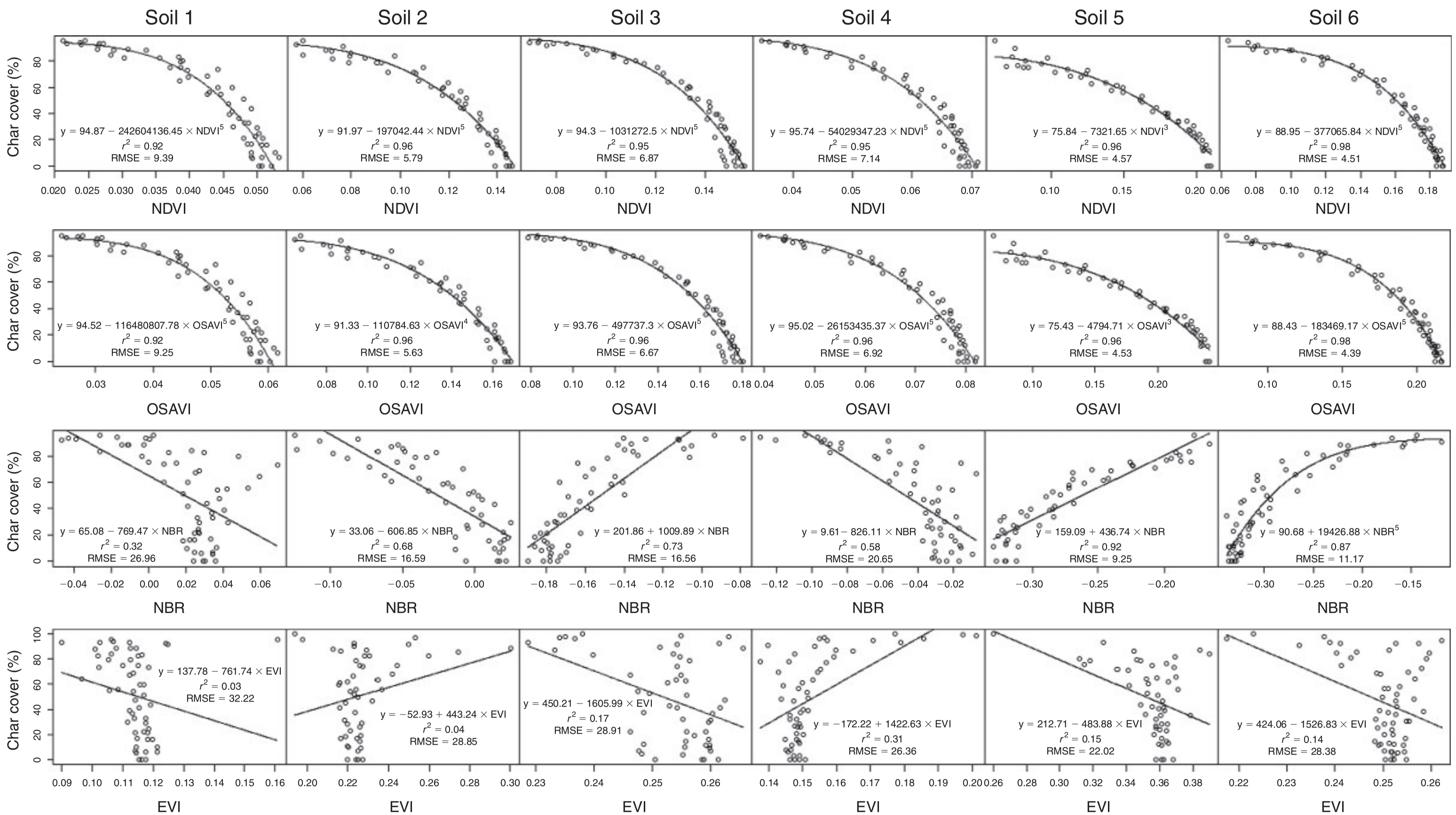

Fig. 3. Variation in selected spectral indices with variations in charcoal (char) cover and soil type. The Normalised Difference Vegetation Index (NDVI) and Optimised Soil Adjusted Vegetation Index (OSAVI) indices produce a generally consistent and strong relationship across all soil types, whereas both Normalised Burn Ratio (NBR) and Extended Vegetation Index (EVI) produce relationship with gradients dependent on the soil type. Models were fitted using the open-source software package *R 2.8.1* (R Development Core Team).

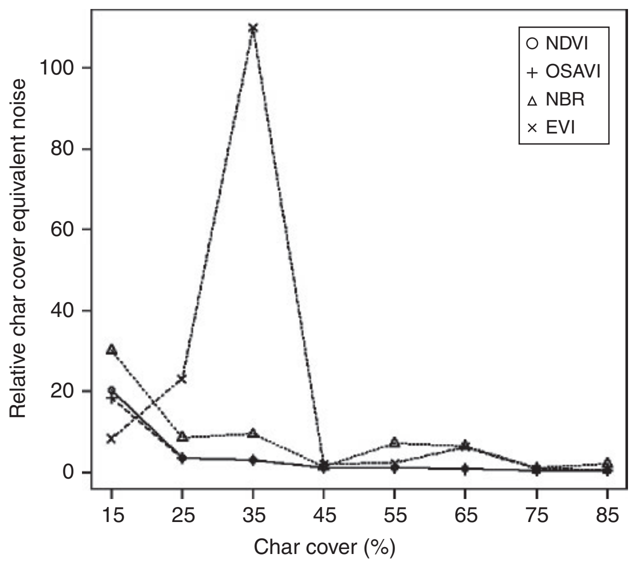

Fig. 4. Relative equivalent noise statistics for each selected index as a function of percentage charcoal cover. See Fig. 3 for definitions.

observation of spectral studies that have evaluated additions of charcoal to bright mineral mixtures (Nash and Conel 1974; Singer 1981; Clark 1983; Clark and Roush 1984). This result suggests that for the charcoal and soil particle sizes used in the current study, the surface components are sufficiently large that there is limited occurrence of multiple scattering between the soils and the charcoal before the light is measured by the sensor (Settle and Drake 1993). Although during real wildland fires, charcoal is typically produced over a wide range of sizes (50 μm–5 mm), the production of very fine charred particles and mineral ash generally results in non-linear mixing if they form intimate mixtures (Smith *et al.* 2005).

The results further show that EVI is relatively insensitive to the deposition of charcoal cover on soils, thus limiting its applicability as an alternative for the remote assessment of post-fire effects. For each of the NBR, OSAVI and NDVI indices, the regressions were generally not linear, thus leading to potential challenges when seeking to scale these results to sensor data of varying spatial resolutions. The multiscale challenges of the NBR-type indices have been observed in prior studies; specifically, the NBR index produces non-linear relationships that vary with applied sensor resolution (van Wagtendonk *et al.* 2004; Holden *et al.* 2010). It seems from the present work that evidence is emerging that NBR may be more sensitive to soil variation than NDVI and OSAVI, which fits with the conventional wisdom (http://earthobservatory.nasa.gov/Features/BAER/, accessed 21 September 2010), but that this may actually be counterproductive from an applications standpoint. NDVI and OSAVI are demonstrating stability across soil types, which argues for using such indices for regional burn severity and recovery mapping, perhaps instead of NBR, especially for broad-scale applications like the MTBS project mapping burn severity of fires across the entire US since 1984 (http://mtbs.gov/index.html, accessed 21 September 2010). Indeed, before the widespread adoption of NBR, the NDVI and similar indices were widely used (Lentile *et al.* 2006) to evaluate both area burned (e.g. Kasischke and French 1995; Razafimpanilo *et al.* 1995; Salvador *et al.* 2000) and the long-term vegetation recovery via analysis of spectral trajectories (e.g. Viedma *et al.* 1997; García-Haro *et al.* 2001; Díaz-Delgado *et al.* 2003; Hicke *et al.* 2003; Turner *et al.* 2003). As such, perhaps such methodologies should be revisited when considering the development of national maps of post-fire effects. These results also suggest that extending this record even further, using Landsat Multispectral Scanner (MSS) imagery dating back to 1972, would be a very feasible and productive venture (Hudak *et al.* 2007). Regardless of the indices selected for such long-term assessments, it is apparent that these results may have important implications for past and current studies seeking to compare long-term trends in severity from NBR-based assessments with climate change drivers (e.g. Holden *et al.* 2010). For the assessment of area burned using spectral methods, maximising the discrimination (or separability) between burned and unburned vegetation is a critical factor (Lentile *et al.* 2009), which may in terms of their application override variations due to soil type.

Prior studies may need to repeat their analyses with indices that are less sensitive to soil type, such as NDVI or OSAVI, to ensure that patterns and trends being observed are not due to variations in the soil background reflectance. These observations will likely have significant implications for studies using multitemporal variants of NBR, especially if there is a considerable change between pre- and post-fire soil coverage. However, given the current wide-scale application of multitemporal methods to characterise severity of fire-affected landscapes, research is warranted to evaluate the magnitude of this effect under the full range of soil cover changes.

Together, these results have consequences for the management and monitoring of large-scale wildland fires. Each of the spectral indices produces different relationships with each soil type, demonstrating that knowledge of the specific soils across the extents of wildland fires is essential to infer the proportional charcoal coverage. We acknowledge that a central limitation of the current study is the particle size and nature of the charcoal used in this experiment. Future research is warranted to re-test these results for charcoal particles with sizes between 50 μm and 1 mm. This experiment should be repeated using charcoal produced through the incomplete combustion of wood, rather than the industrially produced coconut charcoal used herein. Wood charcoal produced through incomplete combustion exhibits spectral reflectance curves closer to unburned wood at large particle sizes (Smith *et al.* 2005), which will likely result in further variations in the near-infrared and short-wave infrared reflectance values beyond those observed in the analysed soils. Although the current study deliberately analysed charcoal and soil in the absence of vegetation in an attempt to decouple the vegetation effects, the addition of this third component may result in non-linearity in the mixing results. The post-fire surface reflectance is often more complex than a mixture of soil, vegetation and charcoal. The surface reflectance can be affected by the presence of unburned vegetation, in addition to patches of soil charring and white mineral ash associated with high fire intensity (Stronach and McNaughton 1989; Shea *et al.* 1996; Roy and Landmann 2005; Smith *et al.* 2005; Roy *et al.* 2010). Topography, canopy structure, soil moisture and structure (including the abundance of organic material) each can have considerable impacts on the measured reflectance (Shea *et al.* 1996; Nagler *et al.* 2000; Roy and Landmann 2005; Verbyla *et al.* 2008). Therefore, subsequent experiments are needed to first simulate under similar controlled laboratory conditions more of these spectral components and associated properties to understand their relative contributions and impacts to the post-fire reflectance. Following those experiments, this research should be extended to prescribed fire field studies where pre-, active, and post-fire data are collected in a coincident manner, such as in the Rx-CADRE experiments (Hiers *et al.* 2009). In these prescribed fire research scenarios, fuels can be burned in a more natural setting but with controls for fire behaviour and fuel characteristics (loading, arrangement, moisture, etc.).

Acknowledgements

This work was supported by the National Science Foundation (NSF) Idaho Experimental Program to Stimulate Competitive Research (EPSCoR) program and by the NSF under award number EPS-0814387.

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Manuscript received 2 June 2009, accepted 1 May 2010