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Evaluating the utility and seasonality of NDVI values for assessing post-disturbance recovery in a subalpine forest

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Abstract Forest disturbances around the world have the potential to alter forest type and cover, with impacts on diversity, carbon storage, and landscape composition. These disturbances, especially fire, are common and often large, making ground investigation of forest recovery difficult. Remote sensing offers a means to monitor forest recovery in real time, over the entire landscape. Typically, recovery monitoring via remote sensing consists of measuring vegetation indices (e.g., NDVI) or index-derived metrics, with the assumption that recovery in NDVI (for example) is a meaningful measure of ecosystem recovery. This study tests that assumption using MODIS 16-day imagery from 2000 to 2010 in the area of the Colorado's Routt National Forest Hinman burn (2002) and seedling density counts taken in the same area. Results indicate that NDVI is rarely correlated with forest recovery, and is dominated by annual and perennial forb cover, although topography complicates analysis. Utility of NDVI as a means to delineate areas of recovery or non-recovery are in doubt, as bootstrapped analysis indicates distinguishing power only slightly better than random. NDVI in revegetation analyses should carefully consider the ecology and seasonal patterns of the system in question.

Keywords MODIS · Remote sensing · NDVI · Disturbance recovery · Forest fire regeneration

Introduction

Fire is a common disturbance throughout the world, and one of the dominant disturbances in many of the world's ecosystems, with major impacts on processes such as soil biogeochemistry, wildlife habitat, carbon storage, and water chemistry. Fires burn approximately 383 Mha globally each year, on average releasing 2,078 Tg of carbon (Schultz et al. 2008). Forest fires are an especially important ecological disturbance because of the role forests play in carbon storage. Forests globally are believed to be a carbon sink, although disturbances shift forests to a carbon source for some time post-disturbance as it takes several years for plant regeneration to compensate and surpass carbon loss from both the fire itself and post-fire debris decomposition (Kashian et al. 2005). Most of that carbon is taken up in recovering vegetation, and in principle, if the burned forest recovers to a forest of similar composition, the carbon balance will be approximately neutral (Kashian et al. 2006). Changes in carbon balance, however, would occur when recovery to the

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dominant forest state is delayed, or where an alternate successional pathway results in a different stable cover type (Holling 1973). For instance, boreal forests can fail to recover post-fire resulting in persistent grassland (Bouchon and Arseneault 2004), as can subalpine forests in the Rocky Mountains (Stahelin 1943; Billings 1969). Thus, it is important to monitor forest recovery (Kashian et al. 2006) for both scientific and management goals.

Remote sensing has great potential for monitoring disturbance recovery due to its inherently spatial nature, repeatability, and ability to observe large extents at fine grains (French et al. 2008; Frolking et al. 2009). Platforms such as Landsat have made repeated measurements over the entire earth's surface since 1972, providing researchers with a 36-year (and counting) timeline of near-continuous reflectance values. The advanced very high resolution radiometer (AVHRR) instrument series, first launched in October, 1978, established the utility of using phenology for vegetation monitoring. Recently, newer satellites such as moderate resolution imaging spectroradiometer (MODIS) have been developed (Townshend and Justice 2002). MODIS provides daily coverage of the earth's surface at resolutions ranging from 250 m to 1 km and, among many different purposes, is optimized to remotely sense vegetation characteristics of use to landscape and regional scale ecologists. One common metric is normalized difference vegetation index (NDVI), which exploits differential reflection between the red and near-infrared portions of the spectrum characteristic of many common surfaces:

$$\mathrm{NDVI} = \frac{\text{near IR} - \text{red}}{\text{near IR} + \text{red}} \tag{1}$$

where near IR is some, or all, of the reflectance of wavelengths from 0.7 to 2.0 μm and red is some, or all, of the reflectance from 0.6 to 0.7 μm. Various sensors exploit different particular sections of those ranges, but the overall trend of vegetation having a high NDVI and non-photosynthetic background (e.g., water or bare ground) having a lower NDVI holds. NDVI was first developed in the 1970s in the Great Plains, USA (Rouse et al. 1973), to reduce the impact of different illumination angles resulting from topography, minimizing artificial differences between, say, north and south facing slopes. Green vegetation typically has an NDVI of ≈0.7–0.8, bare ground ≈0.4, and water ≈0. NDVI has become one of the most common indices used to study vegetation via remote sensing, and although other metrics have been proposed as an improvement (e.g., Jiang et al. 2006), use of NDVI remains commonplace. NDVI was chosen for this study due to its conceptual simplicity, accessibility to non-technical users (it is a standard product for many platforms), comparability to previous platforms (such as AVHRR), and to ease generalization to other studies.

NDVI is commonly used in disturbance ecology to monitor fire impact and recovery (Lentile et al. 2006; Frolking et al. 2009). Fires are often large and/or in remote areas, meaning ground investigation is impractical or impossible, and the synoptic view provided by remote sensing gives an economical means to monitor and map fires throughout the world (Hardy and Burgan 1999; Malak and Pausas 2006; Frolking et al. 2009). Because NDVI can distinguish between bare soil and vegetation cover, the immediate impact of fire (reduced vegetation at a site) can be evaluated using a differencing approach, where a site is compared to itself before the disturbance. Alternatively, a comparison approach may be used, comparing a burned site to a nearby non-disturbed point, and the relative difference is reported (Lentile et al. 2006). Lately, there has been increased interest in using remote sensing to evaluate post-disturbance (such as fire, timber extraction, insect infestation, etc.) forest recovery (Frolking et al. 2009). Several studies have addressed this issue, in areas such as Spain (Diaz-Delgado et al. 2002, 2003; Ruiz-Gallardo et al. 2004), Canada (Goetz et al. 2006), the southwestern USA (van Leeuwen 2008; Casady et al. 2010), the Pacific Northwest (Schroeder et al. 2007), Siberia (Cuevas-Gonzalez et al. 2009), the Amazon (Asner et al. 2004), Indonesia (Wijaya et al. 2010), and a cross-location analysis between Spain, Israel, and the USA (van Leeuwen et al. 2010; also see Online Resource 1).

Many current studies use the recovery of NDVI, or related change metrics, to describe vegetation recovery post-disturbance (Hicke et al. 2003; Diaz-Delgado et al. 2002; van Leeuwen 2008; Cuevas-Gonzalez et al. 2009). However, vegetation recovery does not necessarily mean forest recovery, and when concerned with forest recovery (for carbon sequestration modeling or land management goals), an assumption that NDVI recovery means forest recovery may not be valid (Frolking et al. 2009). Few studies have attempted to tie post-fire ground variables (e.g., seedling recruitment, percent cover of a species of interest, erosion, and biogeochemical attributes) directly to remotely sensed "recovery" metrics, especially in highly seasonal ecosystems. It is imperative that disturbance recovery monitoring be tied to actual ground variables: if NDVI (or any remotely sensed "recovery metric") is not reflective of actual forest recovery (however measured), than it is of dubious value from a managerial perspective. If NDVI can be used to sense forest recovery, it may be useful as an aid in decision making, such as determining when and where to undertake revegetation efforts. In the case of landscapes which may take on alternate stable states, the ability to do these things immediately post-disturbance, or within a short period of years, is imperative.

Questions and hypotheses

This study addressed the concern that NDVI recovery may not be reflective of ecosystem recovery as measured by a return to the same dominant vegetation; in this case the vegetation variable of interest is conifer seedling recruitment. Is NDVI a reliable indicator of forest recovery? Do differences in recovering NDVI levels correspond to differences in the density of recovering forest? As an aid to decision making, can NDVI values be used to distinguish between recovering and non-recovering forests? Seedling recruitment levels were expected to correlate with NDVI. It was also hypothesized that due to the influence of annual forbs, seedling/NDVI correlation would be strongest in spring (immediately post-snowmelt, prior to forb emergence) and fall (post-annual species mortality, before snowfall). Forb cover was expected to correlate with NDVI throughout midsummer. The ability of NDVI to distinguish between recovery and non-recovery and enhance decision making was tested using NDVI data from the year of field sampling, 2010.

Methods

Study area

The study area is in northwestern Colorado, USA (Fig. 1), in the Routt National Forest and Mt. Zirkel wilderness area. The landscape is a subalpine forest, dominated by subalpine fir (*Abies lasiocarpa*), Engelmann spruce (*Picea engelmannii*), and lodgepole pine (*Pinus contorta*), with aspen (*Populus tremuloides*) also common. Sandy loam soil derived from pre-Cambrian parent material (granite and gneiss) is predominant (Snyder et al. 1987). Sampled site elevation ranges from 2,595 to 3,178 m ASL. Typically, snow covers the area from mid-November to early June. The region derives most of its moisture

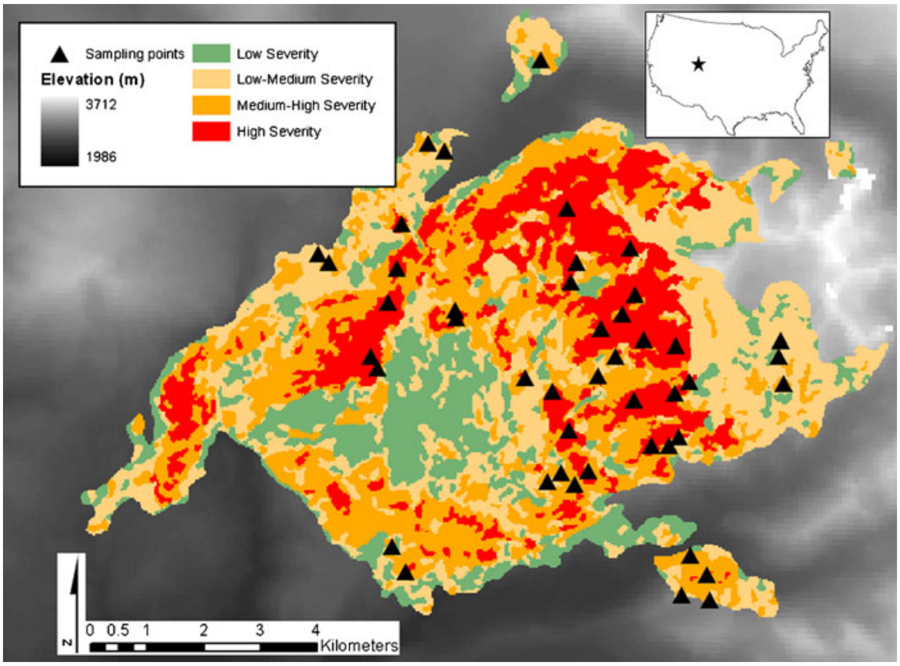

Fig. 1 Location of study area. Site is located in northwestern Colorado, USA. Each sampling point (n=45) consists of two subplots (15 m^2) separated by 75 m (random orientation), for 450 m^2 sampled per point. Fire severity (as defined by USFS NDBR mapping) is shown. All plots were verified as high-severity fire (complete aboveground mortality and organic soil consumption) during the field survey

from snowmelt and summer monsoons. The climate is continental: mean annual temperature of 4.8 C, ranging from −6.0 C in January (mean) to 15.7 C in July (NRCS 2010). In 2002, lightning ignited the Hinman fire, which burned a substantial portion of a previous blowdown (in 1997, see Baker et al. 2002) and surrounding forests. All burned areas used in this study are in areas of high burn severity, i.e., complete aboveground mortality. This limits the influence of residual survivors. The severely burned patches are large, but with variable coniferous regeneration, and therefore a good candidate to test the ability of NDVI to monitor actual forest recovery.

Remote sensing and spatial data

To take advantage of the temporal nature of snowmelt and forb emergence, high temporal resolution imagery was used. MODIS 16-day TERRA NDVI scenes (product MOD13Q1) were acquired from the NASA WIST clearinghouse (wist.echo.nasa.gov), covering the period from February 2000 to December 2010. The TERRA dataset was chosen as it gives coverage of the burned area prior to the fire as well as post-fire. These images are created from bands 1 and 2 (620–670 and 841–876 nm, respectively), collected at a spatial resolution of 250 m. These data are created through a composite methodology which results in the best pixel from each 16-day period being included in the final image (LP DAAC 2010). "Best" is defined by a selection hierarchy. First, all pixels collected (up to 64 for a 16-day period) are screened for quality (i.e., removing pixels obscured by clouds). If more than five quality pixels are retained, the pixel values are interpolated to give a nadir-equivalent reflectance. If less than five quality acquisitions are present for that pixel, the maximum reflectance pixel is used after weighting for viewing angle (favoring pixels collected at closest to nadir). If no high quality observations are available, the maximum reflectance date is used. This results in an image where each pixel has an uncertain acquisition date (or is a composite of dates) within that 16-day window. For convenience, however, the term "date of acquisition" will be used to refer to a single NDVI image, recognizing that each image represents a potential 16-day range. All pixels are reported with a quality flag, so pixels collected under sub-optimal conditions (snow, clouds, etc.) can be removed for analysis. The fire map used in initial plot assignment (Fig. 1) was created by the US Forest Service using Landsat NDBR mapping (not used in analyses). A 30-m digital elevation model (DEM) was acquired from the USGS for the topographical component. Spatial processing was carried out in ArcGIS 9.2 (ESRI 2009).

Ground measurements

Ground measurements were conducted in the summer of 2010. Each site (n=45) consists of two paired plots (15×15 m each, 90 total plots), separated by 75 m. The paired plot design was chosen to better account for variability within a 250-m pixel, as compared to a single, larger plot. Each plot was completely surveyed for conifer seedlings, and at each plot ten randomly placed 1-m^2 quadrats were measured to determine percent cover of forbaceous ("forbs") species. Ten randomly located volumetric soil moisture measurements were taken at each plot. Sites were randomly placed with a minimum spacing of ~500 m. Every site was within a high fire-severity patch, meaning complete aboveground mortality and complete organic soil consumption, minimizing the possibility of residual survivors and ensuring each site started from a common state. Initial plots were randomly located using ArcMap within high-severity burn (Fig. 1), and verified as high severity on the ground (no surviving vegetation, complete mineral soil exposure). Each site represents a complete census of coniferous seedlings for 450 m^2 and the mean of twenty 1-m^2 quadrat estimates of forb cover. Surveys were conducted in August and September, when forb cover peaks. Slope, aspect, and elevation were determined from the DEM, and assigned to a given site based on the bilinear interpolation of midpoint between the two subplots. Aspect was transformed (to "TRASP") using Moisen and Frescino (2002), which creates an aspect index aligned from northeast (coolest, wettest) to southwest (warmest, driest):

$$\mathrm{TRASP} = \frac{1 - \cos\left(\left(\frac{\pi}{180}\right)(\mathrm{aspect} - 30)\right)}{2} \tag{2}$$

Recovery analysis

To link NDVI values directly with actual conifer regeneration, models were created in R (R Development

Core Team 2009) for the relationship between field-measured conifer seedling densities and measured NDVI. All points were inspected for two criteria. First, sites were not significantly spatially autocorrelated for all paired distances present in the data, as evaluated using Moran's I. Second, all sites were located far from any live tree to avoid mixed pixels. While it is impossible, in the heterogeneous environment of a post-fire landscape, to avoid all residual trees, this method ensured that sampled pixels avoided any overtly mixed pixels due to patches of unburned forests. Time-series NDVI values were extracted for each site (extraction point located midway between the paired plots, bilinear interpolation) from 2003 to 2010 for each acquisition (n=184).

Modeling followed a three-step process (Fig. 2a), which was repeated at each date of acquisition: Bad pixels were removed using the MODIS reliability score, topographical influences were removed via partialling, and a generalized linear model (negative binomial distribution) was constructed. In the first step, each site was checked against its pixel reliability score from the particular acquisition date. A score of 0 or 1 (indicating quality pixels) were retained, scores of 2+ (indicating snow or clouds, or otherwise bad data) were removed. This resulted in potentially fewer sites being considered at any given date; if ten or less sites were considered "good," that date was not considered at all. As a result, models constructed were based on between 11 and 45 sites (in practice, it was usually all-or-nothing, as the majority of "bad" pixels resulted from snow and thus affected all pixels equally, and tended to melt out around the same date).

Once the data was subset into quality NDVI scores, a linear model explaining NDVI as a function of elevation, aspect, and slope was constructed. The residuals of this model (representing variance in NDVI unexplained by topography) were used for further analyses. While the index nature of NDVI reduces the influence of differential illumination angles in the sensed reflectance values (e.g., differences in slope and aspect), topography can influence phenology and thus NDVI at a given point in time (Hwang et al. 2011). Therefore, topographical effects are removed in two ways, first through the index and second through statistical partialling out. This creates a very conservative test in that any variance in conifer/forb levels which co-varied with topography

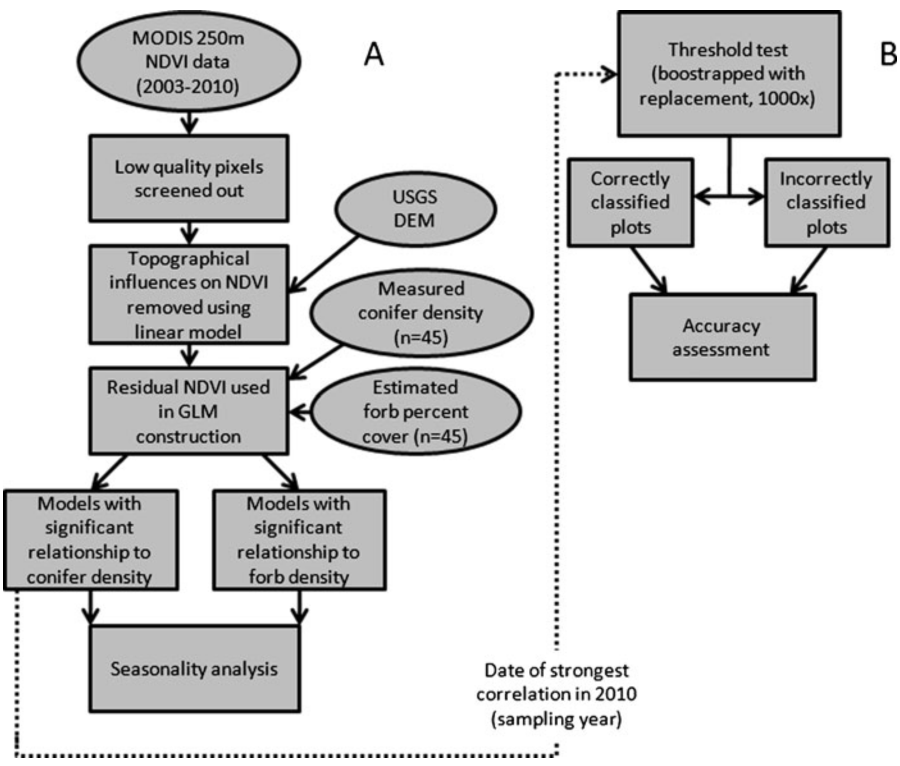

Fig. 2 Flowchart outlining analyses used in this study. **a** Seasonal analysis to investigate trends in relationships between both conifer density and forb cover. **b** Bootstrap testing to determine if NDVI can be used as a means to distinguish coniferous densities above or below a given threshold

was removed prior to testing. This unfortunately reduces the statistical power of the tests, however was considered necessary.

In the final step, a generalized linear model (GLM) using a negative binomial distribution was constructed to predict coniferous seedling counts from residual NDVI. A negative binomial distribution was assumed based on visual analysis of model residuals, and so site count data (number of seedlings/site) were used instead of densities. Counts are transformed to densities in the results for each of interpretation. For percent forb cover, a simple linear model (on residual NDVI) was used as the cover data was continuous and normally distributed. This process was repeated for every acquisition date post-fire (n=183). It is recognized that running multiple models against the same data inflates the possibility of type I errors (false positive), however as the purpose of the testing was exploring seasonal trends, and not finding significance in any particular individual model, this was considered acceptable. Dates with significant relationships between residual NDVI and coniferous seedling counts or percent cover of forbs were retained and tallied. To give a general sense of model accuracy, pseudo-r^2 values for the conifer GLM were calculated using the formula:

$$\text{Pseudo-}r^2 = 1 - \left(\frac{\text{residual deviance}}{\text{null deviance}}\right) \tag{3}$$

Standard Pearson's r^2 are reported for forb data.

The date of best correlation from 2010 (the year of sampling) was used to determine the reliability, accuracy, and utility of NDVI and topographic-based threshold values in assessing conifer regeneration (Fig. 2b). To see if NDVI could be reliably used to distinguish recovering vs. non-recovering coniferous forest, a bootstrapped threshold test was conducted. The complete dataset was sampled, with replacement, 1,000 times. At each iteration, the same procedure as before was followed (removal of unreliable pixels, partialling of topographical effects, and GLM construction). The resultant GLM was used to create a cutoff residual NDVI value separating "recovering" from "non-recovering" using a literature-defined threshold. The bootstrapped sample was then assessed for accuracy. If either the site was above the NDVI cutoff and literature threshold, or below both, it was considered accurately assigned. If it was either above the NDVI cutoff but below the literature threshold, or vice versa, it was considered incorrectly assigned:

$$\text{Accuracy} = \frac{\text{number correct}}{\text{number correct} + \text{number incorrect}} \tag{4}$$

A value of 0.5 would indicate no better than random assignment. The literature-defined threshold was 382 trees/ha from Nyland (≈17 trees/450 m^2; 1998). In extensive work throughout the 1988 Yellowstone burn area, 382 trees/ha was the mean of the group of plots which were failing to recover to any significant density, and Nyland concluded those areas would become isolated tree islands at best, barring extensive competition from graminoid species on future seedlings. Although Nyland (1998) is primarily focused on lodgepole pine forests, lodgepole is a significant component of the overstory and the mechanisms inhibiting future establishment (competition with grassland species) are the same and so 382 trees/ha was considered an acceptable example threshold. In practice, threshold cutoffs would be indentified through a combination of the ecological questions being asked, local knowledge of the system, and management goals.

Results

Seedling recruitment varied considerably between plots, with some plots showing zero seedlings and others showing 2,000 seedlings/ha (mean=316.5, SD=418.9). The regenerating forest was dominated by lodgepole, as expected given the fire and lodgepole cone serotiny, however spruce, a wind-dispersed post-fire colonizer, had a strong presence as well: 58% lodgepole, 26% spruce, 15% fir. Forb cover also varied considerably (mean=34.1%, SD=17.0%), almost entirely dominated by fireweed, *Epilobium angustifolium*. Conifer density was not significantly related to forb cover (Fig. 3). This large range in seedling densities gives a strong recovery gradient, and the lack of correlation ensured independence between conifer and forb models.

Correlations between NDVI and coniferous recovery were limited. Very few significant correlations were seen, primarily in the spring (Fig. 4). The best correlation was seen in the year of measurement (2010), as expected. However, once the effects of

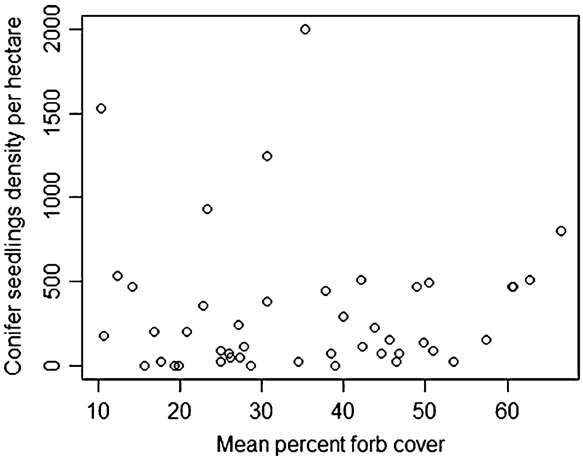

Fig. 3 Relationship between percent cover of forbs and conifer seedling density. The relationship is not significant ($p>0.98$), and thus independence between the two modeling runs can be assumed

topography were removed, the pseudo-r^2 value was only 0.18. Forb cover was more strongly correlated with NDVI, however, consistently showing strong correlations throughout midsummer, even after considering the effects of elevation, slope, and aspect (Fig. 4). The seasonal patterns confirm our hypotheses, with the correlations between conifers and NDVI mainly occurring in the spring, whereas the summer season is dominated by forbs (Fig. 5). The potential for spurious correlations is present because of the repeated testing, but the trends are still obvious despite this potential source of noise.

The bootstrapping procedure to determine the utility of NDVI in differentiating between "recovering" and "non-recovering" demonstrated some distinguishing power. After partialling out the impact of elevation and aspect, NDVI was able to distinguish between recovering or non-recovering plots. The mean accuracy was 0.62 (median=0.63, standard deviation=0.10), slightly better than random assignment (Fig. 6). This accuracy was insensitive to the choice of cutoffs, as several other values (250–750 seedlings/ha) were investigated with only marginal change in accuracy scores.

Discussion

The fire of 2002 had a dramatic impact on NDVI values across a range of sites in the Routt National Forest. Superficially, NDVI appears to have recovered quickly from the fire, with peak summer NDVI indistinguishable between areas with little to no

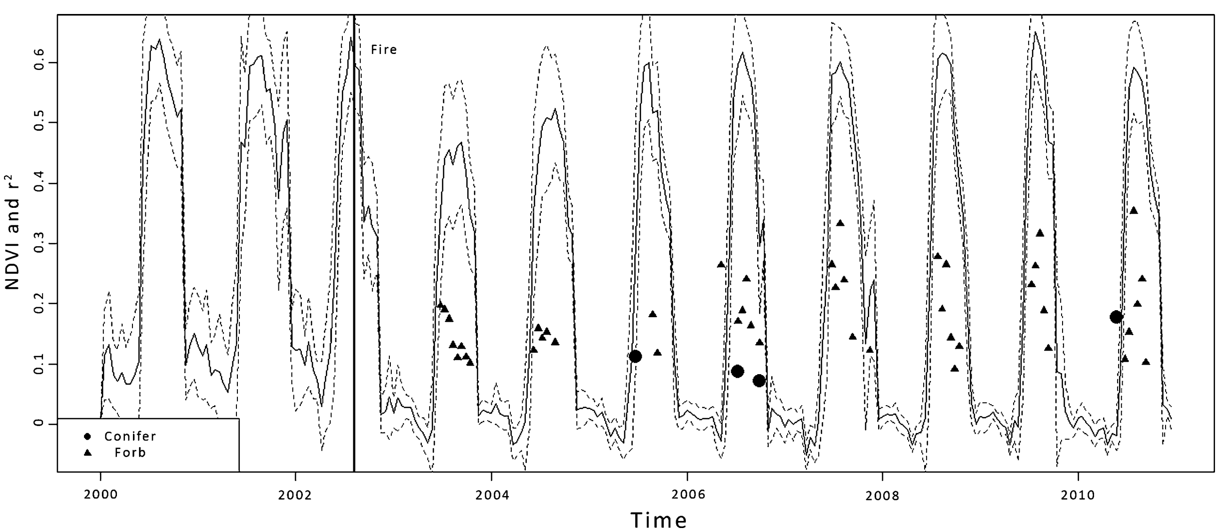

Fig. 4 NDVI trends compared to significant correlations between seedling density and residual NDVI (after partialling out topography). *Black line* is the mean NDVI for all plots, *dashed lines* are ±1 standard deviation. *Symbols* show the pseudo-r^2 (conifers) or r^2 (forbs) for that date. Annual and perennial forb cover dominates every summer, while significant correlations between conifers and NDVI are only seen during green-up or green-down. The *vertical line* is the date of the fire (July–August 2002). NDVI data from 2000 to 2002 is only shown for reference, and not included in the analyses, which included 2003–2010

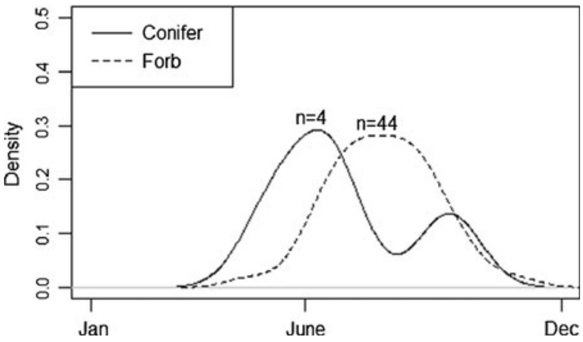

Fig. 5 Seasonal trends in significant correlations between conifer recovery and NDVI (2000–2010), standard density plot. There are reliable correlations between conifer density and NDVI in June, with little correlations otherwise, indicating that early spring is the best time for using NDVI to assess forest recovery. Correlations with percent cover of forbs peaks in midsummer (July/August), likely overwhelming any signal from the coniferous recovery

conifer recovery and areas with strong seedling recruitment; the peak NDVI has essentially recovered to pre-fire levels. This presents problems for assessing post-disturbance vegetation recovery using NDVI values alone. It appears that the flush of forbs in midsummer washes out any differences in NDVI caused by differential recovery to the 2002 fire. The reoccurrence of significant correlations at the same time period every year lends strength to the argument that this correlation is not spurious, and can be used to make ecological inferences.

At the plot scale, assessment of actual conifer recruitment via NDVI seems to be limited. Because the vast majority of seedlings established within 3 years of fire, and growth (especially in lodgepole) can be rapid, it seems likely that correlations between NDVI and seedling density would appear a few years after the fire and continue yearly. Specifically, it seems reasonable to expect NDVI to increase in dense plots in the spring, where conifer densities of 2,000 trees/ha were observed. This "shoulder season" represents the time after snow melt and before aspen leaf eruption and forb growth (typically fireweed, *E. angustafolia*, in this area). After this short time period, the NDVI signal from the forbs drowns out the conifer NDVI signal. Although this relationship was only found in a few cases, as the seedlings continue to grow, this relationship may become more regular. While there may also be a shoulder season in the fall, these analyses were unable to find multiple significant relationships indicating a seasonal trend. This could be due to aspen leaves still present or the significant amount of dead fireweed on the ground, which likely still has a relatively high NDVI (compared to bare ground).

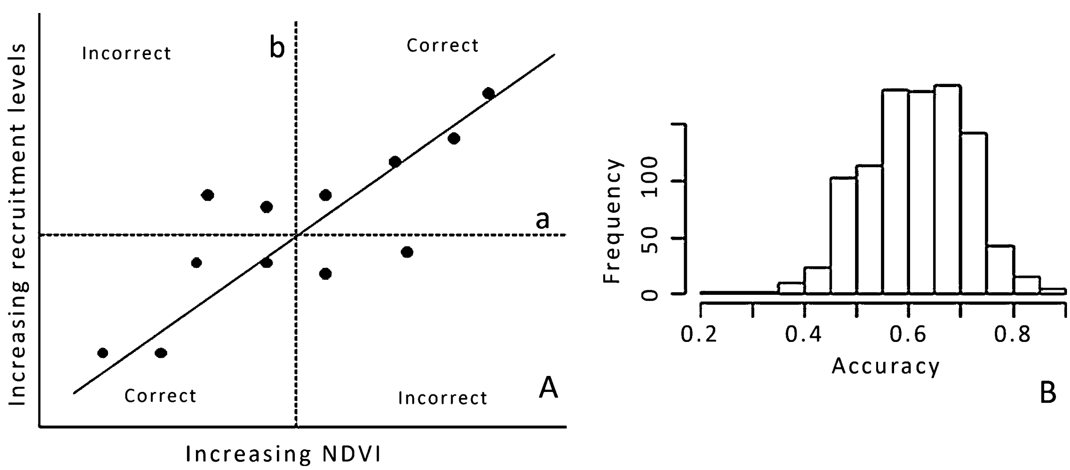

Fig. 6 Method of distinguishing between recovering and non-recovering forest, and results. **a** Methodology (artificial datapoints). As sensed NDVI increases, so does recruitment levels. *Line a* is a given threshold between recovery and non-recovery. The regression line (based on recruitment points) is then used to determine a cutoff NDVI (*line b*) for use in mapping. Quadrants are labeled *correct* or *incorrect* to show which points were correctly classified, counts of correct/incorrect were used in accuracy assessment. Datapoints shown are not actual datapoints, only shown for example. **b** Results of bootstrapping analysis (n=1,000) of classification accuracy; 0.5 indicates essentially as good as random (equivalent points in *correct* and *incorrect* quadrants). Classification of recovery vs. non-recovery (based on Nyland 1998) is better than random assignment

The correlations were weak, once the confounding impacts of topography on NDVI were removed. Conifer seedling density was correlated with elevation (p=0.048), and so removing the influence of elevation entirely represents a conservative move, potentially obscuring the relationship between conifer seedlings and NDVI. However, as topography (especially elevation) has a significant influence on NDVI (Hwang et al. 2011), this accounting was necessary despite the loss of statistical power. It is possible that a similar investigation in areas with less topographical complexity may find different results, due to a more synchronous snowmelt and phenological timing. There were few significant correlations, and some occurred very early in recovery. While the majority of recovering vegetation established quickly post-fire (within 3 years), significant mixing with the ground or other vegetation would occur while the seedlings were quite small, although the significant relationship in the year of sampling (2010) is encouraging. It is also possible that derived phenology-based analyses, such as the slope of green-up (green-up rate) or growing season length, may provide more significant information. However, phenology modeling requires several years of contiguous data and so is not as quickly applied. In addition, phenology analyses are fundamentally based on reflectance values, and so the findings of this study, that reflectance values do not always correlate with forest recovery, are relevant and must be considered.

Given the large pixel size and relatively small footprint of the seedlings, we must consider spectral mixing with soil. Any differences in NDVI are influenced by differences in soil reflectance. Because the soil type is similar across the entire area (sandy loam, see Snyder et al. 1987), differential soil reflectance is likely dominated by soil moisture, which can have a significant effect on NDVI. Influence of soil moisture could be felt in two ways: “Greener” vegetation on moister plots, or the darker soil color influencing NDVI (or a combination of the two). Both can potentially increase NDVI (Huete and Jackson 1988; Todd and Hofer 1998). Thus, the differences between the plots reflectance potentially reflect a combination of vegetation recovery and soil conditions, and that combination may change over time.

Precipitation was similar between all years post-fire (Fig. 7). Seedlings were not significantly correlated with

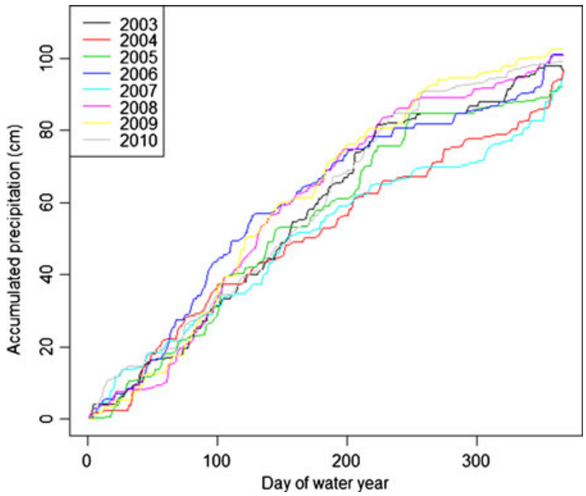

Fig. 7 Precipitation accumulation for each water year following the fire. Water years are defined as October 1–September 31. Data are from the Lost Dog SNOTEL site, located within the burn perimeter. Data are available at the USDA Natural Resources Conservation Service webpage: http://www.wcc.nrcs.usda.gov/snow/

volumetric soil moisture at the site scale (p=0.4), although the mean cover of forbs was (p<0.05). Soil moisture measurements were taken at the time of sampling (July and August), where general drying over the course of the summer may have reduced variation between plots. Spring soil moisture may show a more direct relationship with conifer density. The lack of correlation in the fall could also be due to spectral mixing. Dead and senescing vegetation could raise the albedo within the pixel, which has the effect of reducing NDVI via a decrease in the spectral ratio between red and NIR (Huete et al. 1985). The increase in albedo as result of the summer drying (both in magnitude and range) could also be responsible for the lack of sensitivity of NDVI to seedling density in the fall. Differential soil moisture levels may therefore be adding to the residual NDVI variance, obscuring the conifer signal. As the seedlings get larger, this effect may diminish, however soil mixing will not be eliminated entirely as a variable until canopy closure is achieved.

Stronger conclusions can be made about the relationship between forb cover and NDVI. The annual and perennial forb cover showed consistent correlation with NDVI, even while accounting for elevation, aspect, and slope. This relationship was strongly seasonal, peaking approximately a month after snowmelt and persisting till fall. The caveat on establishment and growth applied to the coniferous modeling does not apply as strongly here; while we do not have cover estimates for the years immediately post-fire, it seems reasonable to assume that percent cover could have been extremely high even in the first year post-fire, as fireweed (a perennial) is an aggressive colonizer, as are the other ruderal species present. Thus, the presence of significant correlations even in the first year post-fire is not a concern. It appears that the thick cover (mean=34%, 17% SD, max=77.6%) of forbaceous plants provides enough photosynthetic capacity to put NDVI at essentially pre-fire levels in midsummer, effectively eliminating the ability of this vegetation index to measure substantive tree recovery.

The ability to make binary recovery/non-recovery decisions is slightly enhanced with NDVI. Using NDVI as a decision tool is better than random assignment, but while significant, the utility of such a slight improvement is questionable. As the forest matures and seedlings begin to overtop the forb layer, NDVI may begin to reflect actual forest recovery and classification may become more accurate and precise. However, lack of substantial tree recruitment soon after disturbance can lead to little tree recruitment for centuries (Stahelin 1943; Lynch 1998) due to moisture competition from graminoids, and planting in grasslands requires more extensive effort with lowered chance for success. If forest regeneration is desired, areas for replanting or other interventions should be identified relatively soon post-disturbance. The example cutoff from Nyland (1998) is just one example of a threshold value, which would in practice be determined locally, dependent on management goals, expert knowledge, species mix, and resources. Actual “thresholds” are more likely a range of densities, where values depend on local factors and seed availability for sod forming graminoids. It is a safe assumption, however, to say that sites with zero seedlings are not likely to recover and sites approaching 2,000 seedlings/ha show strong recovery (Alexander 1987), as seen in this study. Managers should use local knowledge to determine an acceptable level of natural regeneration in planning artificial regeneration/planting efforts before attempting to use NDVI as a recovery monitoring tool. Other values can be found, for instance Jenkins et al. (1998), who divide recovery rates by successional pathway (direct to spruce–fir, spruce–fir with lodgepole seral stage, aspen domination), with densities at 5–10 years ranging from ~750 to 1,150 seedlings/ha (0.075–0.115 seedlings/m^2) in a study in northeastern Utah. In forests where multiple stable states are possible, and the transition point between the states is dependent on early post-disturbance conditions and factors, monitoring recovery rates and pathways is essential, as is using local knowledge and conditions to determine appropriate courses of action (if any). Subalpine grasslands can form an alternate stable state, and thus areas which do not have established seedlings in the first decade post-fire are liable to switch from a conifer-dominated system to a grassland ecosystem (Stahelin 1943; Alexander 1987) or an aspen-dominated ecosystem. Both may be self-maintaining for centuries. Thus, recovery has implications for ecosystem services such as carbon storage and wildlife habitat. NDVI as a classification and mapping tool, at least in the first 8 years post-fire, offers significant, but limited, help in identifying areas which fail to reach desired densities in this test.

Conclusions

The results of this study indicate that use of NDVI in post-disturbance recovery studies must carefully consider the specific attributes of the system in question. Pioneer species, especially forbs, obscure the data, and may give false impressions regarding ecosystem recovery by returning NDVI levels to near pre-disturbance levels while providing little in the way of forest-like ecosystem services (e.g., carbon sequestration, snow catchment). As an aid to management, using MODIS NDVI to distinguish between recovering and non-recovering areas in subalpine forests (while significantly better than random) does not appear to be particularly viable in a practical sense. While the different phenology patterns between forbs and conifers offers a window into early forest recovery, that window is small, at least in the first 8 years post-disturbance.

This study indicates that phenology can be exploited to sense coniferous recovery, and should be tested in other ecosystems. It is likely that every ecosystem will have different temporal windows when actual forest recovery can be distinguished from forbs and other interfering vegetation; some landscapes, particularly relatively aseasonal ecosystems like the tropics, may be more difficult due to the lack of a reliable non-understory period. Other ecosystems, like the boreal forest, which plays a large role in carbon storage, potentially have stronger temporal signals than the subalpine of Colorado, and less topographical complexity. In any disturbance/recovery study, ground measurements relevant to that recovery must be correlated with any remote sensing product used.

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References

Alexander, R. (1987). Ecology, silviculture, and management of the Engelmann spruce-Subalpine fir type in the central and southern Rocky Mountains. USDA Forest Service. Agricultural Handbook 659. Fort Collins, CO, USA.

Asner, G., Keller, M., Pereira, R., Zweede, J., & Silva, J. (2004). Canopy damage and recovery after selective logging in Amazonia: Field and satellite studies. *Ecological Applications, 14*(4), 280–298.

Baker, W., Flaherty, P., Lindemann, J., Veblen, T., Eisenhard, K., & Kulakowski, D. (2002). Effect of vegetation on the impact of a severe blowdown in the southern Rocky Mountains, USA. *Forest Ecology and Management, 168*, 63–75.

Billings, W. (1969). Vegetational pattern near alpine timberline as affected by fire–snowdrift interactions. *Vegetatio, 19*, 192–207.

Bouchon, E., & Arseneault, D. (2004). Fire disturbance during climate change: Failure of postfire forest recovery on a boreal floodplain. *Canadian Journal of Forest Research, 34*(11), 2294–2305.

Casady, G. M., van Leeuwen, W. J. D., & Marsh, S. E. (2010). Evaluating post-wildfire vegetation regeneration as a response to multiple environmental determinants. *Environmental Modeling and Assessment, 15*(5), 295–307.

Cuevas-Gonzalez, M., Gerard, F., Balzter, H., & Riano, D. (2009). Analyzing forest recovery after wildfire disturbance in boreal Siberia using remotely sensed vegetation indices. *Global Change Biology, 15*, 561–577.

R Development Core Team (2009). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, url http://www.R-project.org.

Diaz-Delgado, R., Lloret, F., Pons, X., & Terradas, J. (2002). Satellite evidence of decreasing resilience in Mediterranean plant communities after recurrent wildfires. *Ecology, 83*(8), 2293–2303.

Diaz-Delgado, R., Lloret, F., & Pons, X. (2003). Influence of fire severity on plant regeneration by means of remote sensing. *International Journal of Remote Sensing, 24*(8), 1751–1763.

ESRI. 2009. Environmental systems research institute: ArcGIS version 9.2

French, N., Kasischke, E., Hall, R., Murphy, K., Verbyla, D., Hoy, E., et al. (2008). Using Landsat data to assess fire and burn severity in the North American boreal forest region: An overview and summary of results. *International Journal of Wildland Fire, 17*, 443–462.

Frolking, S., Palace, M., Clark, D., Chambers, J., Shugart, H., & Hurtt, G. (2009). Forest disturbance and recovery: A general review in the context of spaceborne remote sensing of impacts on aboveground biomass and canopy structure. *Journal of Geophysical Research, 114*, 1–27.

Goetz, S., Fiske, G., & Bunn, A. (2006). Using satellite time-series data sets to analyze fire disturbance and forest recovery across Canada. *Remote Sensing of Environment, 101*, 352–365.

Hardy, C., & Burgan, R. (1999). Evaluation of NDVI for monitoring live fuel moisture in three vegetation types of the western US. *Photogrammetric Engineering and Remote Sensing, 65*(5), 603–610.

Hicke, J., Asner, G., Kasischke, E., French, N., Randerson, J., Collatz, G., et al. (2003). Post fire response of North American boreal forest net primary productivity analyzed with satellite observations. *Global Change Biology, 9*(8), 1145–1157.

Holling, C. (1973). Resilience and stability of ecological systems. *Annual Review of Ecology and Systematics, 4*, 1–23.

Huete, A., & Jackson, R. (1988). Soil and atmosphere influences on the spectra of partial canopies. *Remote Sensing of Environment, 25*, 89–105.

Huete, A. R., Jackson, R. D., & Post, D. F. (1985). Spectral response of a plant canopy with different soil backgrounds. *Remote Sensing of Environment, 17*, 37–53.

Hwang, T., Song, C., Vose, J., & Band, L. (2011). Topography-mediated controls on local vegetation phenology estimated from MODIS vegetation index. *Landscape Ecology, 1–16*. doi:10.1007/s10980-011-9580-8.

Jenkins, J., Dicus, C., & Hebertson, E. (1998). Postfire succession and disturbance interactions on an intermountain subalpine spruce-fir forest. In T. Pruden and L. Brennan (Eds.), *Tall Timbers Fire Ecology Conference 20th. Proceedings. Fire in ecosystem management: Shifting the paradigm from suppression to prescription*, (pp. 219–229). Tallahassee, Florida: Tall Timbers Research Station.

Jiang, Z., Huete, A., Chen, J., Chen, Y., Li, J., Yan, G., et al. (2006). Analysis of NDVI and scaled difference vegetation index retrievals of vegetation fraction. *Remote Sensing of Environment, 101*, 366–378.

Kashian, D., Turner, M., Romme, W., & Lorimer, C. (2005). Variability and convergence in stand structural development on a fire-dominated subalpine landscape. *Ecology, 86*(3), 643–654.

Kashian, D., Romme, W., Tinker, D., Turner, M., & Ryan, M. (2006). Carbon storage on landscapes with stand replacing fires. *Bioscience, 56*(7), 598–606.

Lentile, L., Holden, A., Smith, A., Falkowski, M., Hudak, A., Morgan, P., et al. (2006). Remote sensing techniques to assess active fire characteristics and post-fire effects. *International Journal of Wildland Fire, 15*, 319–345.

LP DAAC (2010). These data are distributed by the Land Processes Distributed Active Archive Center (LP DAAC), located at the U.S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center (lpdaac.usgs.gov).

Lynch, E. (1998). Origin of a park-forest vegetation mosaic in the Wind River Range, Wyoming. *Ecology, 79*, 1320–1338.

Malak, D., & Pausas, J. (2006). Fire regime and post-fire NDVI changes in the eastern Iberian Peninsula (Mediterranean basin). *International Journal of Wildland Fire, 15*, 407–413.

Moisen, G., & Frescino, T. (2002). Comparing five modelling techniques for predicting forest characteristics. *Ecological Modelling, 157*, 209–225.

NRCS. (2010). *Snotel data. Natural Resources Conservation Service*. Washington DC: United States Department of Agriculture.

Nyland, R. (1998). Patterns of lodgepole pine regeneration following the 1988 Yellowstone fires. *Forest Ecology and Management, 111*, 23–33.

Rouse, J., Haas, R., Schell, J., & Deering, D. (1973). Monitoring vegetation systems in the Great Plains with ERTS, Third ERTS Symposium, NASA SP-351 I: 309–317.

Ruiz-Gallardo, J., Castaño, S., & Calera, A. (2004). Application of remote sensing and GIS to locate priority intervention areas after wildland fires in Mediterranean systems: A case study from south-eastern Spain. *International Journal of Wildland Fire, 13*, 241–252.

Schroeder, T., Cohen, W., & Yang, Z. (2007). Patterns of forest regrowth following clearcutting in western Oregon as determined from a Landsat time-series. *Forest Ecology and Management, 243*, 259–273.

Schultz, M., Heil, A., Hoelzemann, J., Spessa, A., Thonicke, K., Goldammer, J., et al. (2008). Global wildland fire emissions from 1960 to 2000. *Global Biogeochemical Cycles, 22*(2), GB2002.

Snyder, G., Patten, L., & Daniels, J. (1987). *Mineral resources of the Mt Zirkel wilderness and northern Park range vicinity, Jackson and Routt counties, Colorado*. Washington, DC: US Government Printing Offices.

Stahelin, R. (1943). Factors influencing the natural restocking of high altitude burns by coniferous trees in the central Rocky Mountains. *Ecology, 24*, 19–30.

Todd, S., & Hofer, R. (1998). Responses of spectral indices to variations in vegetation cover and soil background. *Photogrammetric Engineering and Remote Sensing, 64* (9), 915–921.

Townshend, J., & Justice, C. (2002). Towards operational monitoring of terrestrial systems by moderate resolution remote sensing. *Remote Sensing of Environment, 83*, 351–359.

Van Leeuwen, W. (2008). Monitoring the effects of forest restoration treatments on post-fire vegetation recovery with MODIS multitemporal data. *Sensors, 8*, 2017–2042.

Van Leeuwen, W., Casady, G., Neary, D., Bautista, S., Alloza, J., Carmel, Y., et al. (2010). Monitoring post-wildfire vegetation response with remotely sensed time-series data in Spain, USA, and Israel. *International Journal of Wildland Fire, 19*, 75–93.

Wijaya, A., Kusnadi, S., Gloaguen, R., & Heilmeier, H. (2010). Improved strategy for estimating stem volume and forest biomass using moderate resolution remote sensing and GIS. *Journal of Forestry Research, 21*(1), 1–12.