# Detecting Change in Landscape Greenness over Large Areas: An Example for New Mexico, USA

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## Abstract

Monitoring and quantifying changes in vegetation cover over large areas using remote sensing can potentially detect broad-scale, slow changes (e.g., climate change over decades), as well as more local and rapid changes (e.g., fire, land development over weeks and years). A widely used indicator for detecting change in land cover is a measure of greenness, the Normalized Difference Vegetation Index (NDVI), derived from the Advanced Very High Resolution Radiometer (AVHRR). Detecting change in the NDVI, however, can be confounded by time-dependent patterns (e.g., seasonal effects) and variation associated with climate factors. In the present study we provide a method to address these confounding factors by evaluating the NDVI change using autoregression techniques that compare results from univariate (i.e., the NDVI vs. time) and multivariate analyses (the NDVI vs. time and climate variables) for ~314,000 1-km$^2$ pixels comprising the state of New Mexico over an 18-year period (1989−2006).

The ability to detect NDVI trend was greatly improved by including climate variables in the multivariate analyses of the NDVI over time. Specifically, the fraction of pixels with significant NDVI trend (mostly increasing) doubled from 5.2% of the pixels for the univariate autoregression analyses to 11.9% for the multivariate autoregression analyses. The comparisons of univariate and multivariate analyses also revealed that for most of the pixels with a significant NDVI trend in either analysis, the trend was consistent with changes in local factors rather than to broad-scale, slow changes (e.g., climate change); only 0.8% of the pixels had a significant NDVI trend associated with change in the climate variables. This latter finding is somewhat surprising given that several climate variables changed significantly over much of the state during the 18-year period, and the NDVI was significantly related to these variables in the multivariate autoregressions for much of the area. Close examination of several areas suggested that NDVI change in these areas was attributable to wildfires, agriculture, habitat restoration, and tree mortality associated with insect infestation.

Key words: landscape, NDVI change, New Mexico, local factors, climate factors, autoregression model.

## 1. Introduction

The need for monitoring and quantifying changes in vegetation cover over large areas using remote sensing data has been well recognized (Minor, et al., 1999; Lanfredi, et al., 2003; Gurgel & Ferreira, 2003; Nash, et al., 2006; Vogelmann, et al., 2009; Rigge, et al., 2013). Long-term monitoring using simple and inexpensive methods can potentially detect broad-scale, slow changes, such as those caused by climate change over decades, as well as more local and rapid changes such as those caused by fire, agriculture, land clearing, and habitat restoration over weeks and years. Such monitoring can provide environmental decision-makers with early warning signals for widespread general trends as well as a means to identify specific areas where land conditions are degrading or improving.

The Normalized Difference Vegetation Index (NDVI), derived from the Advanced Very High Resolution Radiometer (AVHRR), can be used as a means to monitor vegetation condition over time (Eidenshink, 1992), and is often referred to as an index of greenness. Changes in vegetation can be detected and quantified using the NDVI in combination with current communication technology, interpretation of results using historical data, and expert knowledge (Schmidtlein, 2005; Nash, et al., 2006, 2008). The NDVI has been shown to measure changes in greenness in a number of areas with diverse land cover, including: Oregon, USA (Nash, et al., 2006), USA (Reed, 2006), Europe (Jones, et al., 2008), Morocco (Nash, et al., 2008), and the African Sahel (Anyamba & Tucker, 2005; Herrmann, et al., 2005). Herein, we use a time series analysis for the 1-km$^2$ monthly NDVI to represent greenness for the state of New Mexico, USA.

To use the NDVI as a diagnostic tool to detect change in vegetation cover, it is important to account for time-dependent patterns in the NDVI (e.g., seasonal effects), which are typically pronounced. This can be accomplished using autoregression techniques (described below; Nash et al., 2006, 2008). It is also important to evaluate the influence of climate factors on the NDVI. Climate variables such as precipitation and temperature often strongly influence vegetation physiology and phenology and hence greenness (Bounoua, et al., 1999), and the NDVI has been shown to be related to climate variables, particularly precipitation (e.g., Malo & Nicholson, 1990; Azzali & Menenti, 2000; Kawabata, et al., 2001; Wessels, 2007; Sonfack, et al., 2013). Climate variables may show a general pattern of change over time (USGCRP, 2009), and thus may account for a trend in the NDVI in some areas. Moreover, accounting for the influence of climate variables on the NDVI should improve detection of NDVI change that is not associated with climate change (as represented by selected climate variables) because such change may be masked by variation resulting from variation in climate variables, thus facilitating the identification of areas of degradation or recovery (Wylie, et al., 2008; Gu & Wylie, 2010).

The present study builds on an earlier study of change in the NDVI over time that accounted for temporal dependencies (Nash, et al., 2006) by including climate factors that may influence the NDVI. The primary objectives of the study were: (1) to improve the capability to detect NDVI change over large areas by accounting for climate factors, and (2) to determine whether NDVI change over time is attributable to change in climate variables or local factors such as fire or development. We recognize that some local factors can be influenced by climate factors (e.g., wildfire, insect infestations), and hence climate change. In this paper, we use the phrase "climate change" to refer to the association between NDVI and the climate variables used in our analyses. We conducted the study throughout the state of New Mexico for the 18-year period from 1989 through 2006. Our approach was first to conduct univariate autoregression analysis for the NDVI and selected individual climate variables over time for the ~314,000 1-km$^2$ pixels comprising the state. This allowed an evaluation of the extent and geographic patterns of increase and decrease of both the NDVI and the individual climate variables across the state. We then conducted multivariate autoregression analysis of the NDVI over time with climate variables included in the analysis for each pixel. A comparison of the univariate and multivariate analyses can show the improvement in detection of a significant NDVI trend that can be achieved by including climate variables in the analysis. The comparison also reveals whether a significant NDVI trend is consistent with climate change as the cause of the trend (i.e., for the climate variables in the analysis) or is consistent with change in more local factors as the cause. Finally, we examined several areas with known land cover history to help understand the likely causes of NDVI change at these localities.

Other studies have developed and employed techniques to monitor ecological changes using the NDVI to distinguish climate influences from disturbances (Wylie, et al., 2008; Gu & Wylie, 2010). Their methods were more detailed and comprehensive than our approach (e.g models were validated using ground data), but the approach was restricted to a few dominant vegetation types and required modeling of the reference condition. Our approach was developed with the purpose of being more broadly applicable anywhere, regardless of land cover type, and thus should be easier to apply over large areas such as the western United States.

## 2. Methods and Materials

### *2.1. Site description*

New Mexico spans 314,460 km$^2$ between 32 and 37$^o$ N and 103$^o$ and 109$^o$ W. The topography of New Mexico is diverse, consisting mainly of high plain plateaus (mesas) with numerous mountain ranges, canyon, valleys, and normally dry arroyos and playas. Elevation ranges from 859 to 4011 m (Fig. 1), and the climate is arid to semi-arid. Annual precipitation varies with elevation and season, averaging 500 mm annually at higher elevations and 250 mm at lower elevations (Enquist & Gori, 2008). Precipitation occurs primarily from May through October, comprising 60% to 80% of the total yearly precipitation in the northwestern plateau and eastern plains of the state, respectively. Winter is the driest season with precipitation occurring mostly as snow in the mountains and a mixture of snow and rain at lower elevations. Elevation and season are the major factors influencing temperature. The southern valleys average a frost-free season total of 200 days, whereas the northern mountains average only 80 frost-free days. During the summer, temperatures may exceed 38$^o$ C at elevations below 1524 m (5,000 feet).

The state's land covers (Fig. S1) is dominated by shrubland (48%) and includes significant expanses of grasslands (31%) and evergreen forests (17%) (Fry, et al., 2011).

### *2.2. Data*

We used the AVHRR 1 $km^2$ local area coverage (LAC) data that are available for the continental United States and Alaska for our analysis (Eidenshink, 2006). AVHRR data processing has been ongoing since 1989 (Eidenshink & Faundeen, 1994), and it constitutes the only consistently processed 1 $km^2$ AVHRR data for the globe. Processing of these data include radiometric correction that results from sensor degradation, adjustments for atmospheric effects, and geometric registration accuracy. The 1 $km^2$ AVHRR LAC data are produced from NOAA-11, -14, -16, and -17 satellites. Radiometric corrections are based on sources specific to each satellite (see Table 1 in Eidenshink, 2006). Adjustments for atmospheric effects include corrections for ozone, water vapor absorption, and Rayleigh scattering. Water vapor absorption can reduce near-infrared band reflectance by up to 30%, and Rayleigh scattering and ozone absorption can increase reflectance in the red band by up to 2% (Eidenshink, 2006). Geometric registration is accomplished using image-to-image registration rather than image to map registration because the former improved geometric accuracy. All observations used in the geometric registration must have a root mean square error of less than 1 pixel. On average, 10 satellite passes per week are used to develop the NDVI maximum value composite (MVC) data. The maximum value composite data methods were developed by Holben (1986). The 1 $km^2$ AVHRR LAC data now include 25 years of observations (Eidenshink, pers. comm.)

We used Proc Expand in SAS 9.2 (SAS®, Cary, North Carolina) to substitute for missing values. A data point was considered an outlier if the difference between consecutive NDVI values was more than 20. These outliers were replaced by interpolation from the neighboring values following Groten (1993) and Nash et al. (2006).

The climate variables selected represent precipitation and temperature because these two factors are generally strongly associated with greenness (Wang, et al., 2003; Twumasi, et al., 2011). We also included dew point temperature, which is the temperature at which atmospheric moisture condenses, because it reflects both temperature and moisture conditions and it was shown to be positively related to the NDVI in a study of agricultural and residential areas in Phoenix, Arizona (Stabler, et al., 2005).

We used five climate variables, four of which were original and one of which was derived. The four original variables were monthly averages of precipitation, maximum temperature, minimum temperature, and dew point temperature. The fifth variable was one-month lag precipitation, derived from monthly precipitation. The four original climate factors were obtained from Parameter-elevation Regressions on Independent Slopes Model (PRISM; http://www.prism.oregonstate.edu/products/matrix.phtml, accessed March 2012) in 4-km$^2$ grid cells and were gridded into 1-km$^2$ grid cells using the inverse distance weighted method in ARC-GIS 9.3.1 (ESRI, Redlands, California) to match the NDVI resolution. Downscaling of PRISM climate data from 4 km$^2$ to 1 km$^2$ was applied recently by Thorne et al. (2012). For the model, we used the monthly NDVI, which is the maximum NDVI value of the biweekly NDVI derived by applying MapAlgebra in ARC-GIS 9.3.1.

### *2.3. Statistical methods*

We conducted two types of analyses for each 1-km$^2$ pixel in New Mexico to reduce or account for temporal and climate related noise of the NDVI to reveal long-term trends. First, we conducted univariate autoregression to quantify the temporal trend (slope) for the NDVI and for each of the climate factors separately to identify the general pattern of change for each variable over the 18-year period. The trend direction for each significant pixel was then mapped to identify geographic patterns in the trend direction. Second, we conducted a multivariate autoregression of the NDVI against all the climate predictors and time to reveal the combined effects and relative contributions of climate factors to the NDVI, and the NDVI trend. For these analyses, the sign and significance level of the coefficients were summarized in a bar graph. Time series regression (autoregression) was used in both analyses because errors in temporal data may be time dependent (e.g., consecutive times, annual cycles). If dependency exists, then the standard error of the estimate (e.g., slope) would be inflated if not corrected, and the significance level for the slope and other estimates would not be correct.

#### 2.3.1. Univariate Autoregression

This analysis addressed trend in the NDVI and the individual climate factors over the 18-year period. For each 1-km$^2$ pixel, the autoregression model (Proc Autoreg; SAS/ETS, 1999) with stepwise selection for the significant autoregressive error was fitted to the observed values to define the direction and p-value for the slope as:

$$Y_t = \theta_o + \theta_1 * Time + \mu_t \qquad 1a$$

$$\mu_t = \sum_{t=1}^{k} \rho_i \mu_{t-i} + \varepsilon_t \qquad 1b$$

$$\varepsilon_t \sim IN(0, \sigma^2) \qquad 1c$$

where $Y$ is one of the individual time series variables: monthly NDVI, monthly precipitation, monthly maximum or minimum temperature, or monthly dew point temperature (n=216 months).

The fitted autoregression model for the observed variable ($Y_t$) is the structural part, which is the same as that of an ordinary least square regression model (OLS; $\theta_o + \theta_1 * Time$), and the autoregressive error ($u_t$). Coefficients $\theta_o$, and $\theta_1$ are the intercept and the slope with time, respectively. The time series error term, $u_t$, may be autocorrelated. The autoregressive error model (Equation 1*b*) will account for such autocorrelation where the term $\sum_{i}^{k} \rho_i u_{t-i}$ is the summation of the significant autoregressive parameter ($\rho$) times lagged error(s), and $k$ is the order of significant lags in the model. The error term, $\varepsilon_t$, from the autoregressive error model is normally and independently distributed with mean of zero and variance $\sigma^2$ (Equation 1c). We present an example of the fitted autoregression model for the observed monthly NDVI data for one pixel (Fig. 2). The fitted autoregression model in this example accounted for dependence at four lags. The slope ($\theta_1$) quantifies the rate and direction of change for each variable over 18 years. We used a significance level of p = 0.05 to test whether the slope differed from zero.

### 2.3.2. Multivariate Autoregression

A multivariate autoregression model relating the NDVI to all climate predictor variables and time was built for each pixel as:

$$NDVI_t = \beta_o + \beta_1 RF_t + \beta_2 RF_{t-1} + \beta_3 T\min_t + \beta_4 T\max_t + \beta_5 DP_t + \beta_6 Time_t + \mu_t \qquad 2a$$

$$\mu_t = \sum_{t=1}^{k} \rho_i \mu_{t-i} + \varepsilon_t \qquad 2b$$

$$\varepsilon_t \sim IN(0, \sigma^2) \qquad 2c$$

where $RF_t$ is precipitation at month $t$, $RF_{t-1}$ is precipitation for previous month (i.e., one-month lag precipitation), *Tmin* is minimum temperature, *Tmax* is maximum temperature, *DP* is dew point temperature, and ε is the error term. The right side in Equation 2*a*, excluding the autoregression error ($\mu_t$), is known as the structural term of the model, and the summation of both terms constitute the predicted value. The estimates ($\beta_i$*'s*) for each variable quantify the magnitude and direction of the relationship between the NDVI and each variable over the 18-year period. The coefficient of Time ($\beta_6$) is the temporal trend of the NDVI after accounting for climate variables. We chose blocks of pixels that have either significant increase or decrease ($p < 0.05$) in greenness for closer examination on a local scale. Information from literature and consultation with local experts were used to examine our results.

We considered the potential that collinearity among climate variables may confound the results. However, our primary interest is the significance of the coefficient for the time variable (i.e., NDVI trend). If time is not correlated with any of the climate variables, the time coefficient variance will not be affected by the collinearity among the climate variables (Wooldridge, 2006). From a random sample of 29 pixels, the correlation between time and each climate variable was low ($|r| \leq 0.15$, $r^2 \leq 0.02$). Consequently, we kept all predictors in Equation 2.

### 2.3.3. **Discrimination between the Effects of Climate Change and Local Factors on the NDVI Change**

A comparison of the results of the univariate and multivariate analyses for each pixel enables discrimination between whether a significant NDVI trend is associated with either climate variables (and hence, climate change) or local factors (e.g., fire, agriculture, development), because climate variables are included in the multivariate analysis but omitted in the univariate analysis. Specifically, we test the hypothesis that a significant NDVI trend is associated with change in climate variables, and consider the alternate hypothesis that local factors are responsible for the trend. We do this by evaluating four possible outcomes for the significance of the NDVI trend in the two analyses. A significant NDVI trend is indicated by a significant time coefficient, i.e., $\theta_1$ in the univariate analysis (Equation 1*a*) and $\beta_6$ in the multivariate analysis (Equation 2*a*). The four possible outcomes and inferences for each are as follows:

Outcome A. NDVI trend is significant in both the univariate and multivariate analyses. There are two possible cases for trend direction:

1. NDVI trend direction is the same for both analyses. This finding is not consistent with the hypothesis that climate change was the cause of the NDVI trend because the trend was significant regardless of whether climate variables were included in the analysis. Thus, this finding is consistent with the alternate hypothesis that local factors like wildfire or agriculture are the cause of the significant NDVI trend.

2. NDVI trend direction differs between the two analyses. This pattern did not occur in any pixel in the study; hence, we do not consider this case further.

Outcome B. NDVI trend is significant in the univariate analysis, but not in the multivariate analysis. This finding is consistent with the climate change hypothesis because the trend became not significant when climate variables were included in the multivariate analysis.

Outcome C. NDVI trend is not a significant in the univariate analysis, but is a significant in the multivariate analysis. This finding is not consistent with the climate change hypothesis because climate variables were included in the multivariate analysis. Thus, the finding is consistent with the alternate hypothesis that local factors are the cause of the significant NDVI trend in the multivariate analysis. Plausibly, trend in the univariate analysis was not significant because the variation in the NDVI associated with variation in climate variables in this analysis masked the influence of local variables on the NDVI.

Outcome D. Trend is not significant in either the univariate or the multivariate analyses. Thus, there is no evidence for a temporal trend in the NDVI.

## 3. Results of Univariate and Multivariate Analyses

### *3.1. **Temporal trends in the NDVI and climate variables in univariate analyses***

The NDVI did not change significantly over the 18-year period for most of New Mexico in the univariate analyses (Fig. 3A). Only 5.2% of the area showed a significant change, and most of this (4.4%) was an increase (Table 1). Areas with significant change were scattered throughout the state. The greatest concentrations of significant increase were in the forested mountains of Torrance, San Miguel, and Santa Fe counties, whereas the greatest concentration of significant decrease was in the mountains of Rio Arriba County.

Among the climate factors evaluated in the univariate analyses, only the temperature variables showed much change during 1989–2006 (Table 1; Fig. 4). Minimum temperature showed a striking pattern of increase, with 67% of the pixels significantly increasing and only 2% significantly decreasing (Table 1; Fig. 4B). Maximum and dew point temperatures also showed predominantly increasing trends, with 20% and 8% of the state showing significantly increasing trends, respectively, and < 1% of the state showing decreasing trends (Table 1; Figs. 4A, 4C). The geographic patterns of change differed among the three temperature variables. Minimum temperature increased significantly throughout much of the state, whereas areas of significant increase in maximum temperature were concentrated in the northern mountains and in the mountains along the Arizona-New Mexico border (Fig. 4A), and areas of significant increase in dew point temperature were concentrated in three arch-like clusters extending across the south-central part of the state (Fig. 4C). For precipitation, virtually no pixels showed a significantly increasing trend, and <1% showed a decreasing trend (Table 1; Fig. 4D). There was no obvious association between the distribution of pixels with significant change in the NDVI and the distribution of pixels with significant change in any of the climate variables (compare Figs. 3A, 4).

### *3.2.* ***Association between NDVI and climate variables in multivariate analyses***

The NDVI was significantly related to one or more climate variables in the multivariate autoregressions for much of New Mexico (Fig. 5). The NDVI was predominantly positively associated with four of the five climate variables. Particularly frequent positive and significant associations were for 1-month lag precipitation (83% of pixels) and maximum temperature (80% of pixels); virtually no pixels showed significant negative associations for these two variables. Monthly precipitation and dew point temperature also showed predominantly positive associations with the NDVI, with 42% and 30% of pixels showing significant positive associations, respectively. In contrast to these positive associations, the NDVI was predominantly negatively associated with minimum temperature (54% of the pixels).

### *3.3.* ***Temporal trends in the NDVI in multivariate analyses***

The inclusion of climate variables in the multivariate autoregression analysis greatly increased the extent of area identified with significant NDVI change over the 18-year period. The NDVI changed significantly for 11.9% of the pixels in the multivariate autoregression

(Table 2; Figs. 3B, 5), whereas it changed significantly in only 5.2% of the pixels in the univariate autoregression (Table 1; Fig. 3A). The predominant direction of change in the multivariate autoregression was an increase in the NDVI (Figs. 3B, 5).

A clear association between the distribution of NDVI change and elevation or land cover type was not evident (compare Fig. 3B with Fig. 1 and Fig. S1, respectively). Nevertheless, many of the larger conspicuous areas of positive change coincided with forested mountainous areas (e.g., in Otero, Sierra, Torrance, San Miguel, and Santa Fe counties) and with the agricultural or grassland areas on the eastern fringes of the state. Moreover, the area of greatest concentration of pixels with significant decrease in the NDVI was in the mountains of Rio Arriba County.

### *3.4.* ***Discrimination between the roles of climate change and local factors on the NDVI change***

In the comparisons of the NDVI trend between the univariate and multivariate analyses, the outcomes were consistent with local factors as the predominant cause of NDVI change rather than climate change (Table 2). The most frequent outcome was Outcome D (87.37%; Table 2), i.e., no trend in the NDVI in either analysis. The next most frequent outcomes were Outcome C (7.44%) and Outcome A (4.43%). For Outcome A, all pixels were Case 1 (i.e., trend direction was the same for both the univariate and multivariate analyses). These two outcomes (i.e., C and A1) comprise all the pixels significant for NDVI trend in the multivariate analysis (11.86%), and are both consistent with local factors being the cause of the NDVI trend rather than climate change. Only 0.77% of the pixels showed Outcome B, the outcome consistent with climate change as the cause of the significant NDVI trend. The pixels with Outcome B tended to be concentrated in mountains in Carson National Forest in the central northern part of the state (Fig. S2).

## 4. **Evaluation of Selected Areas for Cause of NDVI Change**

Below we explore examples of areas with significant change in the NDVI where sufficient information was available to infer the likely cause for the change.

### *4.1. Agriculture*

Agricultural areas, which are mostly irrigated, are sparsely distributed in New Mexico, occurring primarily near the Rio Grande, Pecos, and San Juan rivers, and near the eastern border with Texas (Fig. S3). Greenness significantly increased during the study period in several agricultural areas. An example is the block of green pixels south of the San Juan River in San Juan County (Fig. 3B), an area within the Navajo Indian Agriculture Project (Gorman & Lansford, 1975). An increase in the NDVI was also found in this area for a six-year period (1989-1994), a change that occurred in association with a substantial increase in areal extent of crop production and changes in canopy density related to crop rotation (Minor, et al., 1999). This group of pixels belongs to outcome A (Figs. 3B, S4). The decline in greenness west of the Navajo Agricultural land is apparently in response to mining and associated land reclamation activities (Minor, et al., 1999).

Increase in greenness associated with irrigated agriculture is also evident in scattered patches east of the Cibola Mountains within the Estancia Basin in Torrance County (Figs. 3B, S3). This increase may have resulted from increased efficiency of agricultural water use following the implementation of precision application methods for crop irrigation (EBWPC, 2008). Other areas of increased greenness in agricultural areas occur along the eastern border with Texas from Union to Lea counties, and west of the Pecos River within Eddy and Chaves counties (Figs. 3B, S3). The pixels in these areas belong to outcomes A and C (Figs. S3, S4).

### *4.2. Fires and post fire greenness gains*

Fires can have profound effects on the NDVI, with either decreasing or increasing trend depending on when the fire occurred within the time period evaluated. A conspicuous example of fire effects is the Cerro Grande fire that occurred in May 2000. The fire began as a prescribed fire in Bandelier National Monument (eastern Sandoval County), but spread far beyond the intended extent, a process enhanced by drought conditions and wind (Mynard et al., 2003). The wildfire took 15 days to contain and burned 192 $km^2$ of forest- or woodland-covered land in Los Alamos and neighboring counties. Within the burn polygon identified by BAER (2000), more than 70% of the vegetation was lost, and tree mortality was more than 80%; moreover, many stressed trees subsequently died within three years (Miller & Yool, 2002).

A large fraction of the pixels within the Cerro Grande Fire showed a significant decline in the NDVI during the study period, whereas none showed a significant increase (Fig. 6). This general pattern of decrease is associated with a pronounced decrease in the NDVI at the time of the fire followed by a reduced NDVI for many years. This is evident in examinations of the NDVI for individual pixels, such as the one depicted in Fig. S5. This pixel showed a significantly decreasing NDVI trend over the 18-year study period in the multivariate analysis (green line in Fig. S5). However, multivariate autoregression analysis on the pre- and post-fire NDVI separately showed significantly increasing trends both before and after the fire. In another pixel (Fig. S6), enough recovery in the NDVI occurred during the years following the fire that the trend over the 18-year period (green line in Fig. S6) was not significant. Like the previous pixel (Fig. S5), the analysis of trend pre- and post-fire both showed significantly increasing trends. The NDVI change pixels associated with the Cerro Grande fire belong primarily to outcome A (Figs. 6, S4).

### *4.3. Invasive species and restoration*

Greenness increased significantly in a number of pixels in the floodplain in the Bosque del Apache National Wildlife Refuge, Socorro County, during the study period (Fig. 7). The area of the increased NDVI is associated with restoration of riparian habitat in the floodplain that began in the 1960s (Busch, et al., 1992; Taylor & McDaniel, 1998), and a subsequent wildfire. Restoration activities included reactivation of an abandoned river channel, replacement of over 800 ha (~2000 acres) of saltcedar with cottonwood trees and grasses (Robert, 2005; Taylor & McDaniel, 1998), and production of several crops for wildlife (*http://www.fws.gov/refuges/profiles/index.cfm?id=22520M; http://library.fws.gov/refuges/bosque.pdf*). In 1996 a wildfire occurred that consumed hundreds of hectares of riparian woodland and sandsage shrubland (Fig. 7). The fire initially resulted in conversion from lush green cottonwood woodland to burned stems and bare ground (see photographs in *http://www.nmnaturalhistory.org/assets/files/Education/Cirricula/Chapter_6_Comp.pdf*). In less than two months after the fire, however, tree roots sprouted, and forbs and grasses emerged, resulting in extensive ground cover within two years. The NDVI change pixels related to restoration and fire in refuge belong primarily to outcome A (Figs. 7, S4).

The refuge also includes areas with significant NDVI decrease in Chihuahuan Desert scrub vegetation between the river flood plain and Interstate Highway 25 (red pixels in Fig. 7). This reduction may have resulted from lowering of the water table. Drought and human use of water have decreased the amount of water flowing in the Rio Grande River. For example, since 2002 drought alone has reduced the flow from north of New Mexico to the Rio Grande by 17% (Guido, 2012).

### *4.4. Tree mortality due to insect infestation*

A number of forested areas in New Mexico have suffered significant tree mortality and defoliation from bark beetle infestation (USDA FS, 2010). A conspicuous example is in Carson National Forest and adjacent lands (Fig. 8). Areas of tree mortality are largely coincident with areas of significant NDVI decline (Fig. 8), suggesting that bark beetle infestation has been the cause for much of the NDVI decrease in this area. Rising temperatures and drought exacerbated the pre-existing smaller areas of bark beetle infestation (Breshears, et al., 2005). Minimum and maximum temperature increased significantly during the study period in the area shown in Fig. 8, whereas precipitation decreased significantly in parts of it (Fig. 4). The NDVI change pixels shown in Fig. 8 belong primarily to outcomes A and C (Figs. 8, S4).

## 5. General Discussion

Two important benefits were achieved by including climate variables in the multivariate analysis of the NDVI over time. First, the ability to detect NDVI trend was greatly improved. Specifically, the fraction of pixels with a significant NDVI trend approximately doubled from 5.2% of the pixels for the univariate analyses to 11.9% for the multivariate analyses. This increase apparently accrued because variation in climate variables contributed noise that masked the trend in the NDVI in the univariate analyses for 7.4% of the total pixels (i.e., Outcome C; Table 2). The second benefit is that the comparison of univariate and multivariate analyses provided a way to distinguish between NDVI trends associated with climate change (as represented by the climate variables included in the analyses) and trends associated with local factors (e.g., wildfire, agriculture, restoration). Local factors predominated in these comparisons. Specifically, of the 12.63% of the pixels in which NDVI trend was a significant in either the univariate or multivariate analyses (i.e., sum of Outcomes A, B, and C in Table 2), most of these (11.86%) comprised Outcomes C and A1 -- outcomes that are consistent with local factors as the likely cause of the NDVI trend. Only 0.77% had Outcome B, the outcome that is consistent with climate change as the cause.

The finding that only a small fraction of New Mexico had a significant NDVI trend that was associated with climate change is somewhat surprising given that several climate variables changed significantly over much of the state during the 18-year period, and the NDVI was significantly related to these variables in the multivariate autoregressions for much of the area. The three temperature-related climate variables showed significant increase from 1989 to 2006 over much of New Mexico, whereas precipitation showed no change except for small areas in the northern part of the state. This general pattern of increase in temperature in the state is consistent with other studies of climate change in western North America. Annual temperature increased in New Mexico from 1951 to 2006 by $0.9^{o}$ C (Robles & Enquist, 2011). An increasing trend in daily minimum was higher than daily maximum temperatures in Canada (Vincent & Mekis, 2006) and in western and central North America (Robeson, 2004). This finding is consistent with our finding of a greater extent of New Mexico with significantly increasing monthly minimum temperature than with monthly maximum temperature. By contrast, though, precipitation in the United States and the southwestern U.S. has increased over the past five decades by 5% and 17%, respectively (Robles & Enquist, 2011), which is not consistent with our finding of < 1% of the pixels with significant change in monthly precipitation during 1986−2006 in New Mexico.

The NDVI in the multivariate autoregression analyses was significantly related to each of the climate variables analyzed for large fractions of New Mexico. Thus, given that much of the variation in the NDVI could be accounted for by variation in climate variables, it is not surprising that a significant NDVI trend was detected with much greater frequency for the multivariate analyses that included climate variables in comparison to the univariate analyses that excluded them. The NDVI was most frequently and positively related to previous monthly precipitation (83%), and to a lesser extent (40%) to monthly precipitation. This is consistent with Notaro et al. (2010) who found that green-up of grasses occurs several weeks after precipitation. The NDVI was also positively related to maximum temperature (80% of pixels) and to dew point temperature (30% of pixels), but it was generally negatively related to minimum temperature (53% of pixels). The positive association with maximum temperature seems reasonable as temperature can increase vegetation growth (Notaro, et al., 2010), and dew point reflects both temperature and moisture conditions (Lawrence, 2005). The positive association between the NDVI and maximum temperature presumably reflects the predominant effect of maximum temperature on the NDVI throughout the year, as warmer than average temperatures during summer months would be expected to reduce the NDVI. We have no explanation for the predominantly negative association between the NDVI and minimum temperature in the multivariate analyses. The negative association between the NDVI and minimum temperature becomes evident only when the effects of maximum temperature, which is correlated with minimum temperature, are removed by the multivariate analysis.

The specific cause for NDVI change in a given area can only be accomplished with detailed knowledge of land cover change in the area. Unfortunately, such data are not readily available for most areas. Our evaluation of several areas with such information, however, provided some understanding for the patterns of the NDVI change in those areas. The effects of fire can yield either an increase or decrease in the NDVI depending on when the fire occurred within the time period examined. That is, a fire early in the period will likely yield an increase in the NDVI as vegetation recovers (e.g., following the Cerro Grande Fire of 2000), and a fire late in the period will likely yield a decrease (e.g., Cerro Grande Fire when analyzed over the period 1989-2006). NDVI increase in association with agriculture often occurs in response to expansion of cultivated area (e.g., south of San Juan River), although a decrease in the NDVI would be expected with abandonment of cultivation. Wetland restoration appears to be typically associated with NDVI increase as vegetation cover increases (e.g., Apache del Bosque National Wildlife Refuge), whereas the NDVI can decrease dramatically in response to insect infestation resulting in tree defoliation and mortality (e.g., northwestern Rio Arriba County).

A general geographic pattern of NDVI change in the state was not evident. Significant changes occurred at nearly all elevations and in all major land cover classes, and the extent of areas with significant change ranged from isolated pixels to groups of hundreds of pixels. Nevertheless, several conspicuous areas of NDVI change occurred in forested mountains, and the direction of change was primarily increasing. We speculate that this pattern of increase occurred due to vegetation growth over the 18-year period with either a general lack of wildfires or a general lack in the second half of the period. The NDVI trend direction in the mountains of Rio

Arriba County, however, was decreasing rather than increasing. It is possible that much of this resulted from drought conditions, as this was one of the few areas in the state where precipitation decreased significantly (Fig. 4D), and this ultimately resulted in tree defoliation and mortality from bark beetle infestations. Moreover, it is in this area that the few pixels with a significant NDVI trend associated with climate change occurred.

In conclusion, monitoring changes in greenness over time using remote sensing potentially can be useful in identifying long term trends resulting from climate change or anthropogenic activities on the ground. The present study shows that the greenness index, the NDVI, is often significantly related to climate variables reflecting precipitation and temperature, and these relationships are not necessarily intuitive. Consequently, climate factors may confound the ability to detect areas of NDVI change not associated with climate factors. By including climate variables in a multivariate analysis of the NDVI over time, the detection of areas with significant NDVI change can be much increased. Moreover, a comparison of analyses with and without climate variables can be used to distinguish between areas of NDVI change associated with climate change and areas associated with other factors. Once the latter areas are identified, they can be evaluated for causes of change such as fire or fire recovery, change in agricultural extent or practices, invasive species encroachment or management, land restoration actions, and insect infestations. This approach can be applied over large areas such as U.S. states or regions.

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## Table Titles

Table 1. Percent of total pixels with significant increasing or decreasing trend in the univariate analyses for the NDVI and for each of the climate variables. Significance level is $p<0.05$.

Table 2. Frequency of outcomes in comparison of NDVI trends between univariate and multivariate analyses for 313,817 1-km$^2$ pixels in New Mexico.

## Figure Legends

Fig. 1. Elevation and counties in New Mexico. Major rivers (blue lines) from left to right: (top) San Juan, (bottom) Gila, Rio Grande, Pecos, and Canadian Rivers.

Fig. 2. Monthly observations for the NDVI for 1989 to 2006 in one 1-km$^2$ pixel in New Mexico (closed circle in the map). The blue line connects the observed values (n=216). The fitted univariate autoregression model (i.e., predicted NDVI; red line) is the sum of the trend (green line; $\theta + \theta_1 * t$ in Equation 1*a*) and the autoregressive error term ( $u_t$ in Equation 1*b*). For this pixel, the significant autoregressive errors were at lags (i.e. monthly intervals) 1, 11, 12, and 17, and the predicted NDVI = $114.56+0.08*\text{time}+0.48\,u_{t-1}+0.16\,u_{t-11}+0.21\,u_{t-12}+0.16\,u_{t-17}$.

Fig. 3. Pixels (1 km$^2$) with significant temporal trend for the monthly NDVI from 1989 to 2006 in New Mexico, determined by (A) univariate autoregression (Equation 1*a*) and (B) multivariate autoregression (Equation 2*a*). Sample size is 216 for each pixel. Green indicates significant ($p<0.05$) increase in greenness (i.e., NDVI); red indicates significant decrease in greenness. Counties and rivers as in Fig. 1.

Fig. 4. Pixels (1 km$^2$) with significant temporal trend for monthly climate variables from 1989 to 2006 in New Mexico determined using univariate autoregression (Equation 1*a*; n=216

for each pixel). Green indicates significant increase; red indicates significant decrease. Variables are (A) average monthly maximum temperature, (B) average monthly minimum temperature, (C) average monthly dew point temperature, and (D) average monthly precipitation.

Fig. 5. Summary of relationship direction and significance level between the NDVI and climate variables and time in multivariate autoregression analyses (Equation 2*a*) for ~314,000 1-$km^2$ pixels in New Mexico. Variables are average monthly maximum temperature (Tmax), minimum temperature (Tmin), dew point temperature (DP), precipitation (Prcp), previous month's precipitation (Lag[Prcp]), and time. Data are summarized for pixels with significantly ($p<0.05$) positive association between the NDVI and the subject variable (+sig), not significantly positive association (+nsig), not significantly negative (-nsig), and significantly negative (-sig).

Fig. 6. The 2000 Cerro Grande Fire polygon (heavy black outline; from http://www.fs.usda.gov/detail/r3/landmanagement/gis/, Santa Fe fire history: last accessed July 2013). The fire polygon lies mostly in Los Alamos County (light black lines). Green pixels indicate significant increase in the NDVI over time (multivariate autoregression); red pixels indicate significant decrease in the NDVI over time (multivariate autoregession). Labeled symbols A and B are the locations of the pixels used in Figs. S5 and S6, respectively showing NDVI behavior over time.

Fig. 7. Change in greenness in the Bosque del Apache National Wildlife Refuge (black polygon) in Socorro County. Blue line is the Rio Grande River; red line is Interstate Highway 25; brown polygon indicates boundaries of the 1996 wildfire (provided by Mara Weisenberger, U.S. Fish and Wildlife Service, Las Cruces, New Mexico). Inset map shows the location of the Refuge.

Fig. 8: Tree mortality from insect infestation in 1998 to 2006 (black hatching), and pixels with significant decrease in the NDVI (red color) in multivariate autoregression, in northwestern Rio Arriba County. No pixels in this view showed significant increase in the NDVI. Inset map shows the several segments of Carson National Forest (blue polygons).

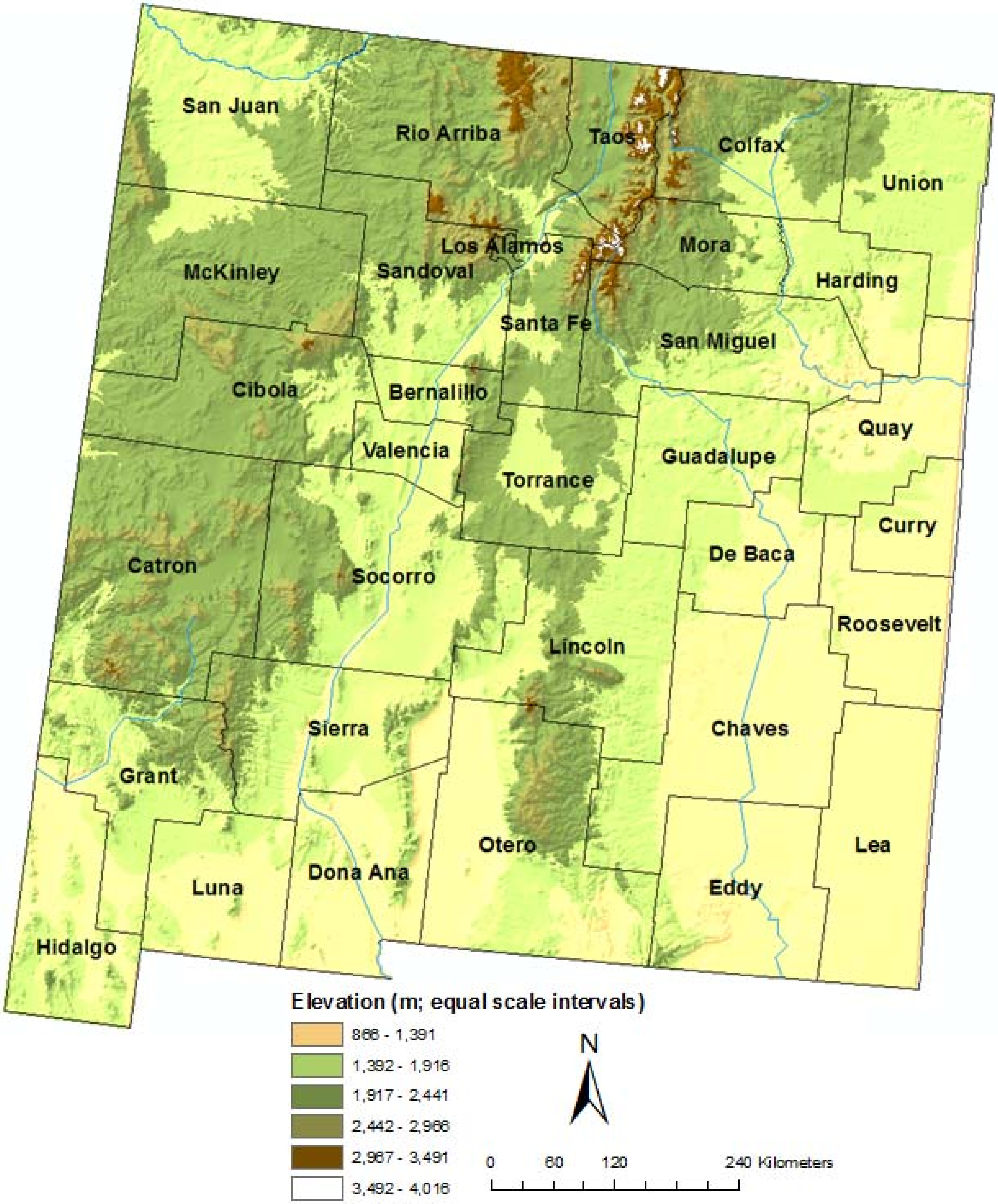
Table 1. Percent of total pixels with significant increasing or decreasing trend in the univariate analyses for the NDVI and for each of the climate variables. Significance level is $p<0.05$.

| Variable | Increase | Decrease | Total |
|---|---|---|---|
| NDVI | 4.43 | 0.77 | 5.20 |
| Minimum temperature | 66.94 | 2.24 | 69.18 |
| Maximum temperature | 20.36 | 0.67 | 21.03 |
| Dew Point temperature | 8.23 | 0.04 | 8.27 |
| Precipitation | 0.0 | 0.74 | 0.74 |

Table 2. Frequency of outcomes in comparison of NDVI trends between univariate and multivariate analyses for 313,817 1-km$^2$ pixels in New Mexico.

| NDVI Trends in Univariate Analysis | NDVI Trends in Multivariate Analysis | | |
|---|---|---|---|
| | Significant | Not Significant | Total |
| Significant | Outcome A<br>4.43% | Outcome B<br>0.77% | 5.20% |
| Not Significant | Outcome C<br>7.44% | Outcome D<br>87.37% | 94.80% |
| Total | 11.86% | 88.14% | 100.00% |

Figure 1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Taos
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McKinley
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Mora
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Santa Fe
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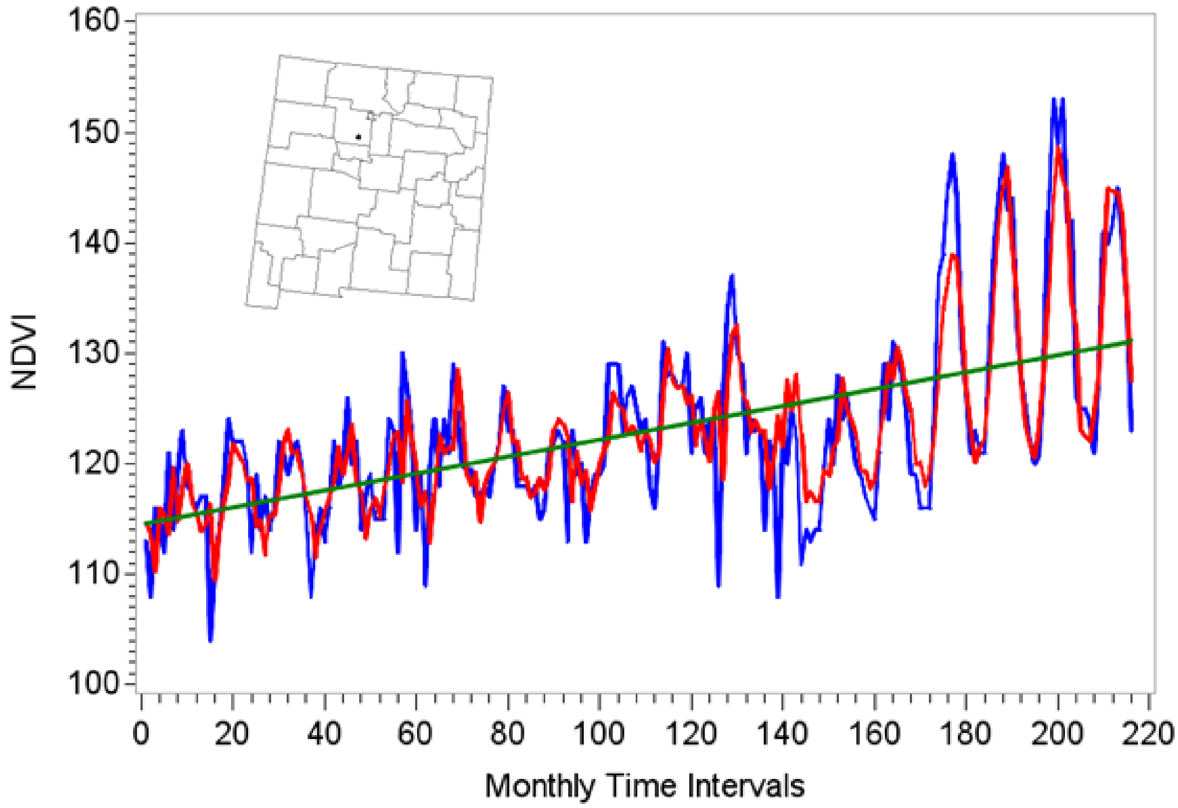
Cibola
Bernalillo
Quay
Valencia
Torrance
Guadalupe
Curry
Catron
Socorro
De Baca
Roosevelt
Lincoln
Chaves
Sierra
Grant
Otero
Lea
Dona Ana
Luna
Eddy
Hidalgo
Elevation (m; equal scale intervals)
866 - 1,391
1,392 - 1,916
1,917 - 2,441
2,442 - 2,966
2,967 - 3,491
3,492 - 4,016
N
0
60
120
240 Kilometers

Figure 2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Monthly Time Intervals
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80
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140
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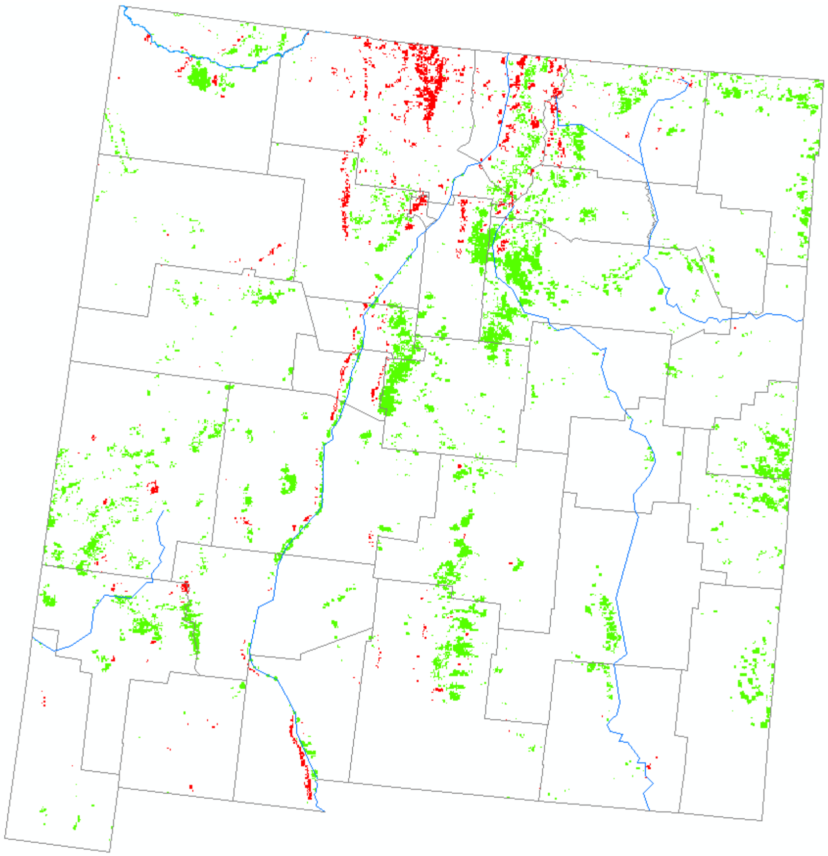
180
200
220

Figure 3

A



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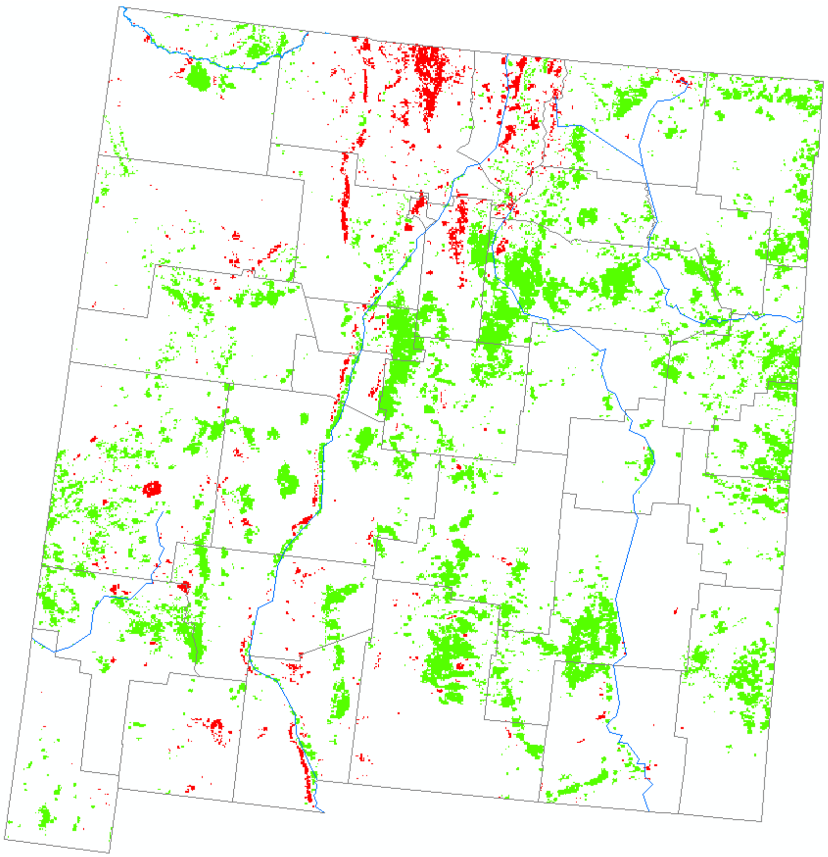
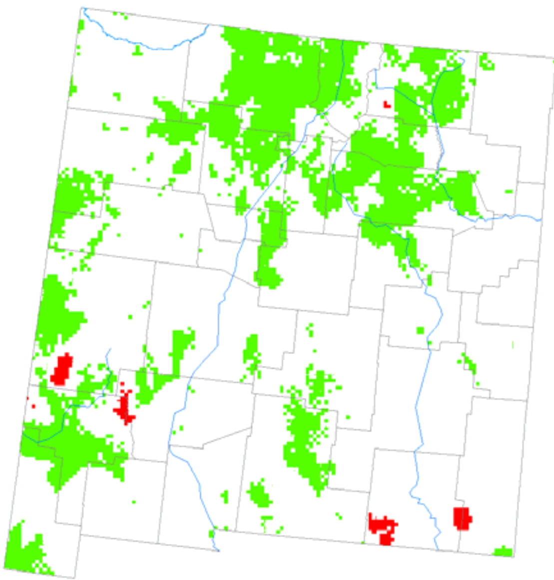


Figure 4

A



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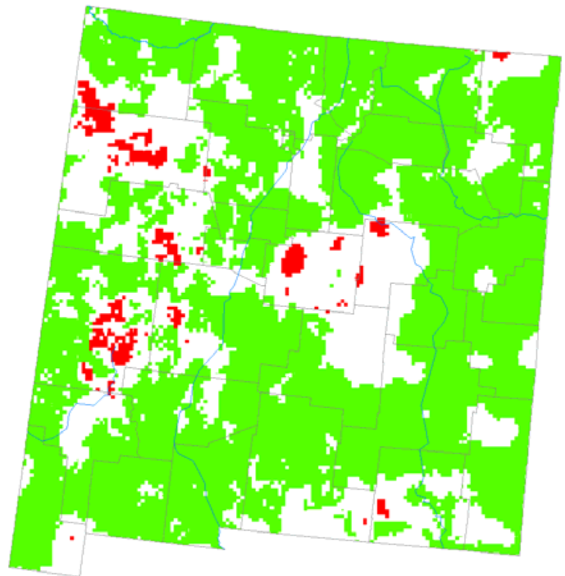

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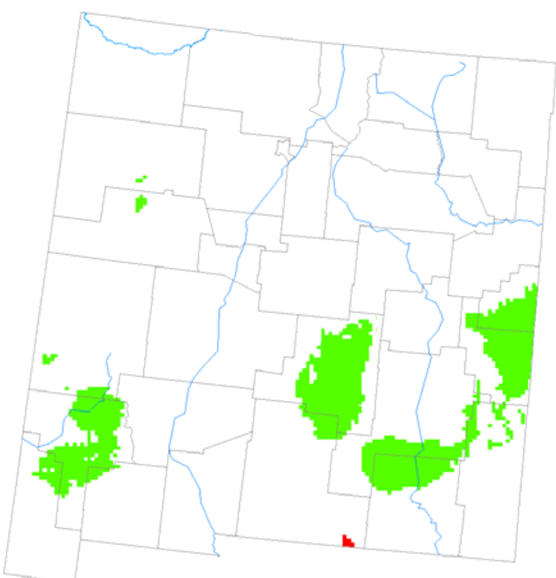

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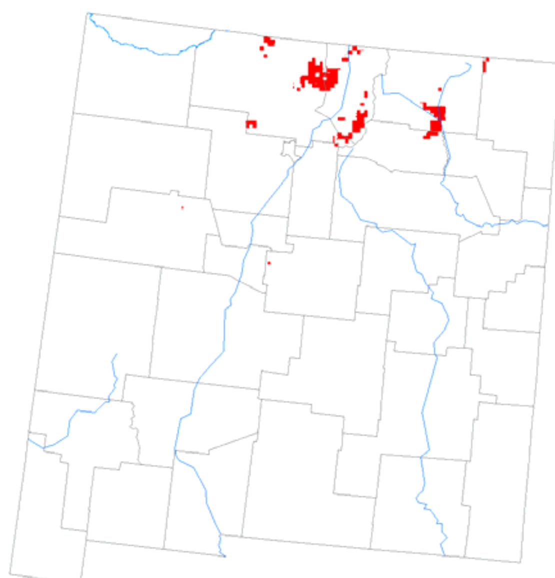
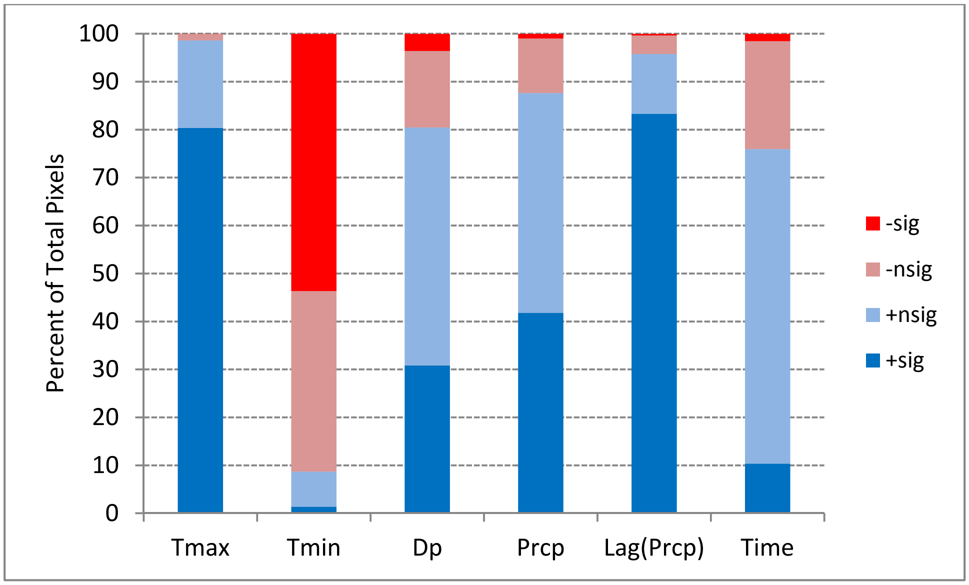


Figure 5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90
80
70
60
50
40
30
20
10
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Percent of Total Pixels
Tmax
Tmin
Dp
Prcp
Lag(Prcp)
Time
-sig
-nsig
+nsig
+sig

Figure 6

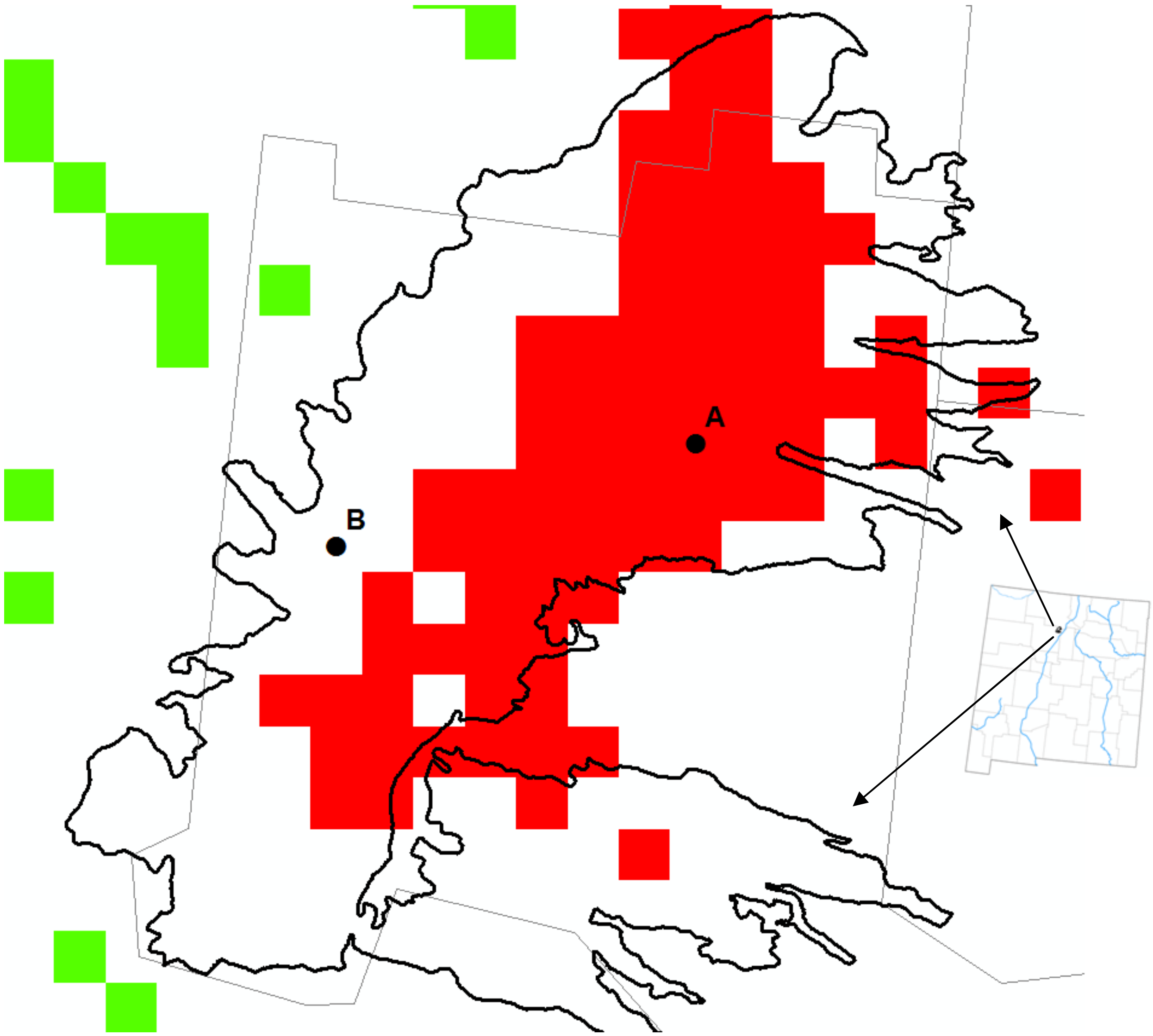


Figure 7

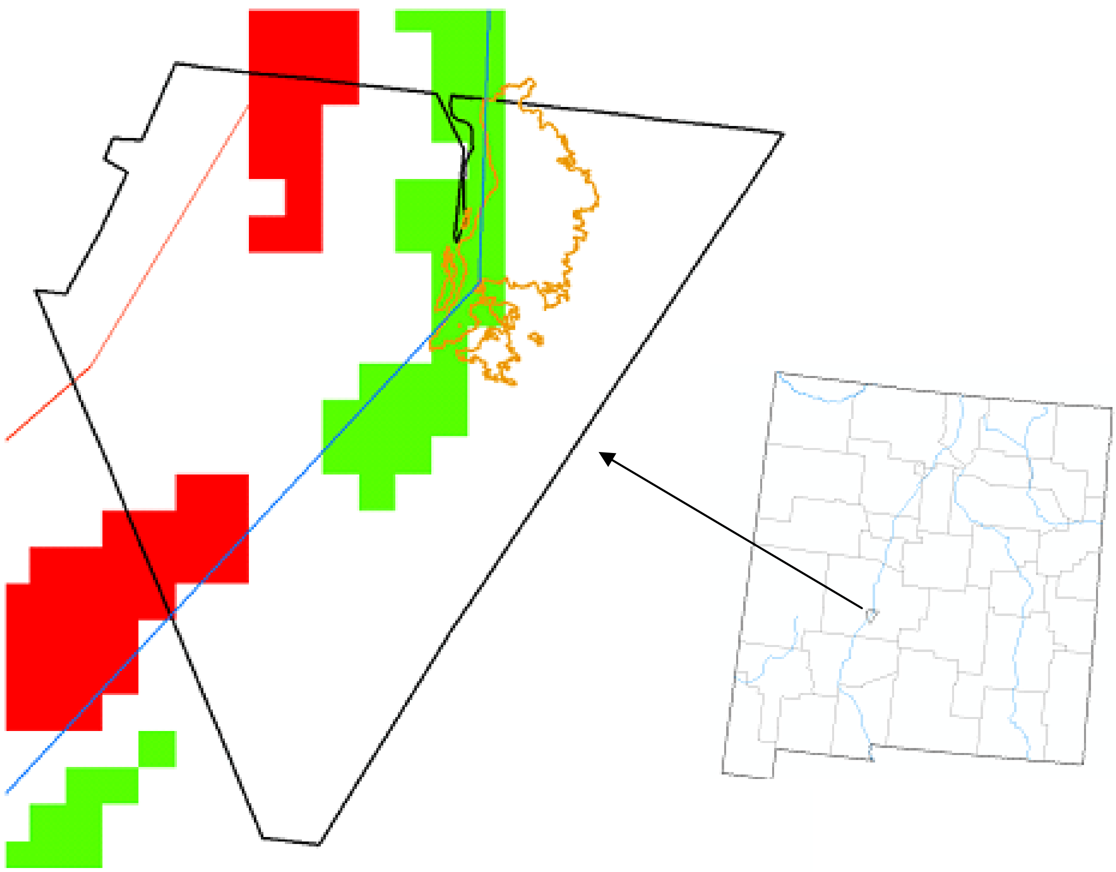
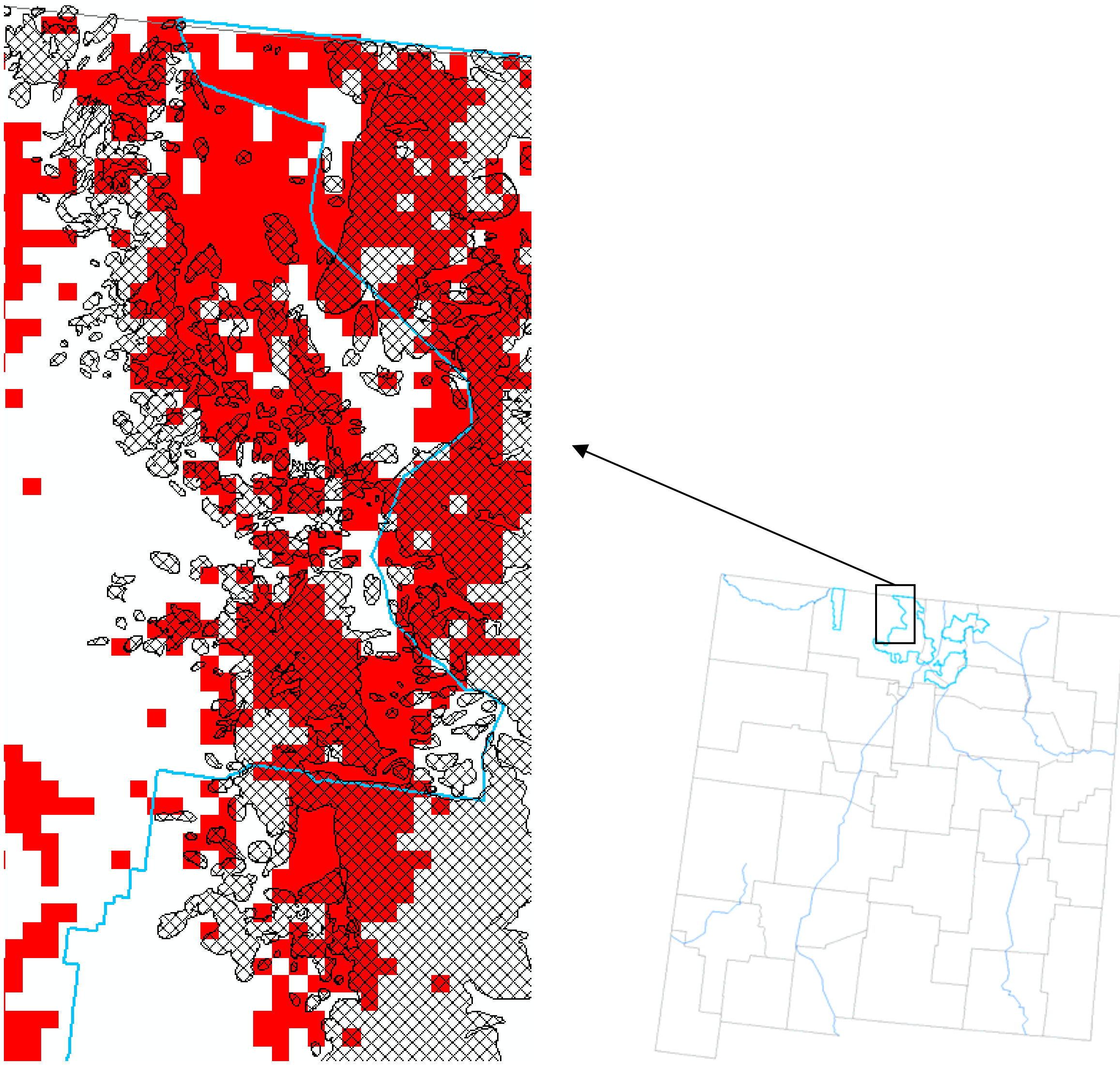


Figure 8



**Detecting Change in Landscape Greenness over Large Areas:**

**An Example for New Mexico, USA**

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## Supplementary Data

## Supplementary Figures

This section present the land cover for New Mexico (Fig. S1), local changes in land cover, and results from the univariate and multivariate regression models are presented in this section. Distribution of pixels with outcomes in the comparison of NDVI trend between the univariate and multivariate analyses showing local or climate change are presented in Fig. S2 & S4. Example of local changes such as agriculture and fire are presented in Fig. S3& Fig. S5. For closer look to the Response of NDVI in a pixel to fire (local changes) contrasted with other pixel without fires are presented Figs. S5&S6.

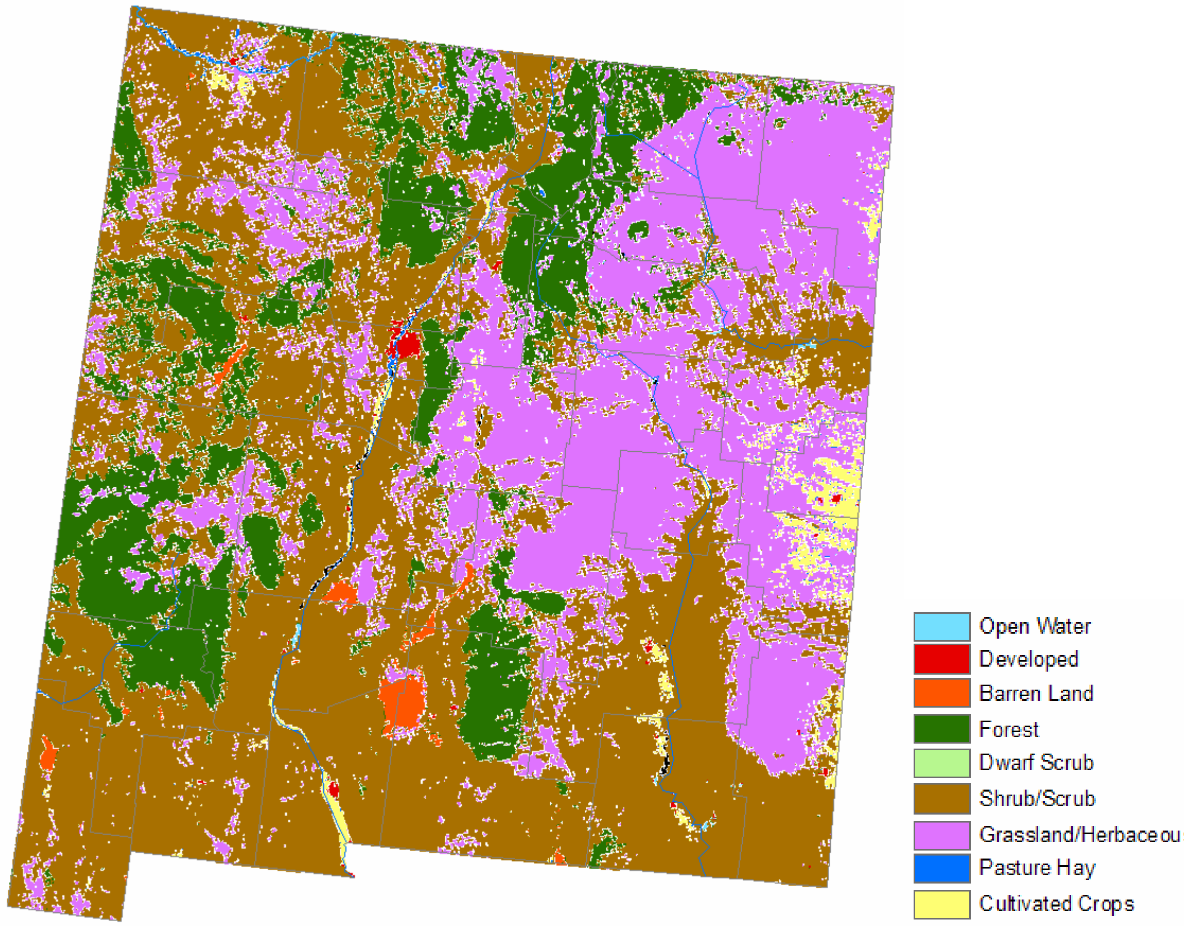


Fig. S1. Land cover for New Mexico. Data from National Land Cover Database (Fry et al., 2011). Counties and rivers as in Fig. 1.

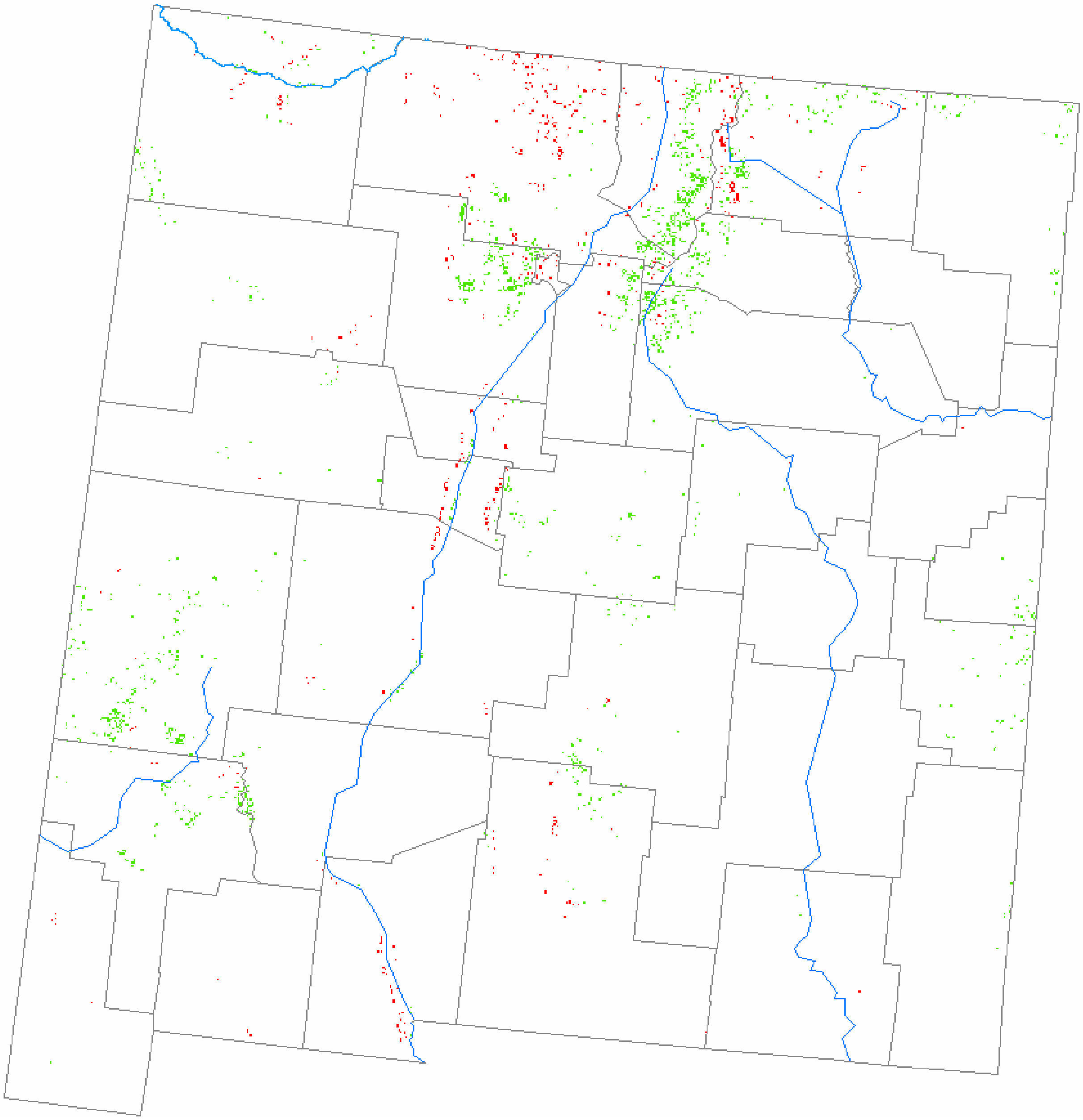

Fig. S2. Distribution of pixels with Outcome B in the comparison of NDVI trend between the univariate and multivariate analyses. In Outcome B, NDVI trend is significant in the univariate analysis and not significant in the multivariate analysis. Outcome B is consistent with climate change as the cause of the significant NDVI trend. Green indicates a significant increase in

NDVI in univariate analysis; red indicates trend a significant decrease in NDVI.  Counties and rivers as in Fig. 1.

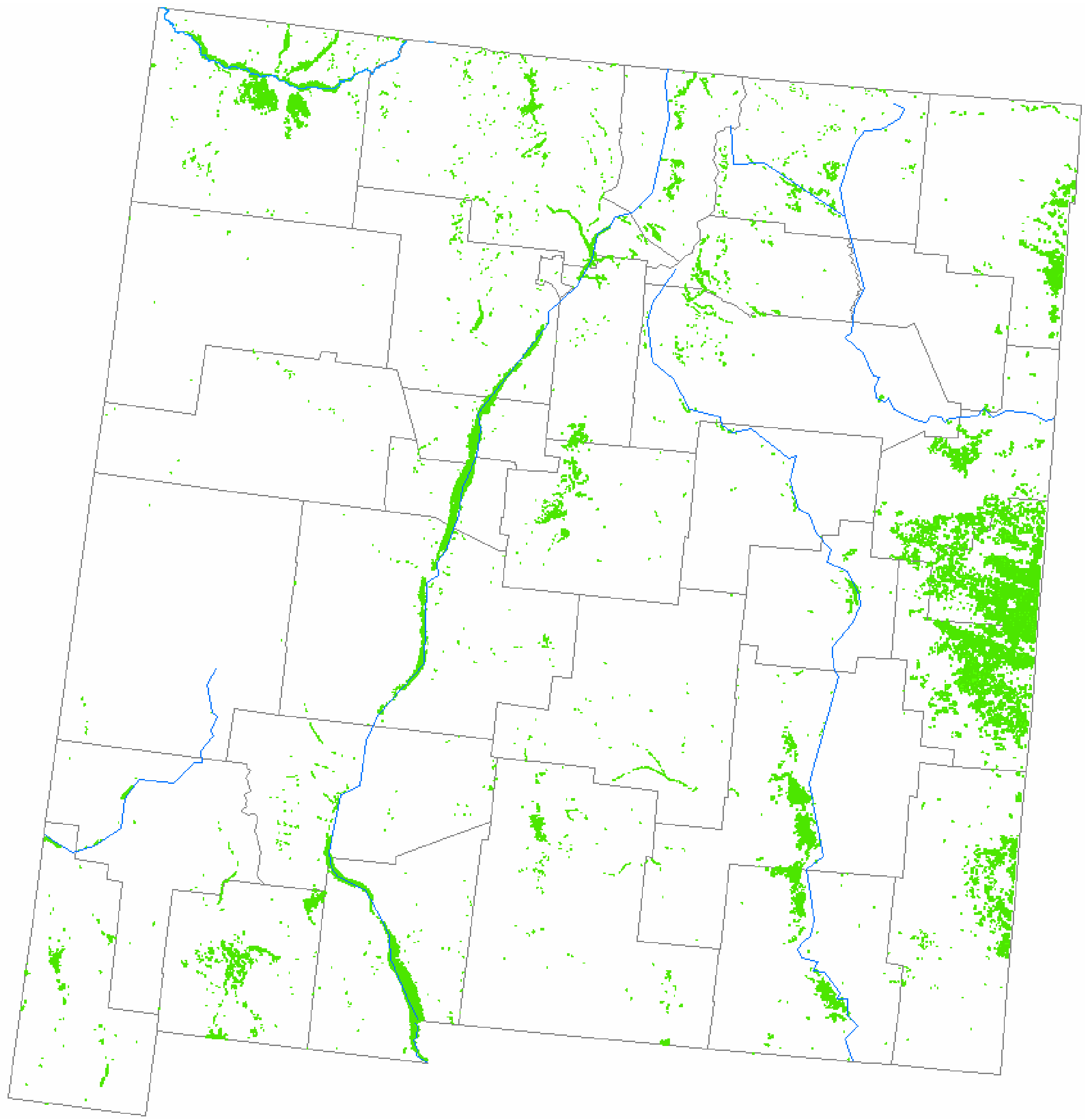

Fig. S3.  Irrigated cropland for New Mexico.  Data were derived from 2006 National Land Cover Database and provided by Kerri Mich, U.S. Natural Resources Conservation Service, Albuquerque, New Mexico.  Counties and rivers as in Fig. 1.

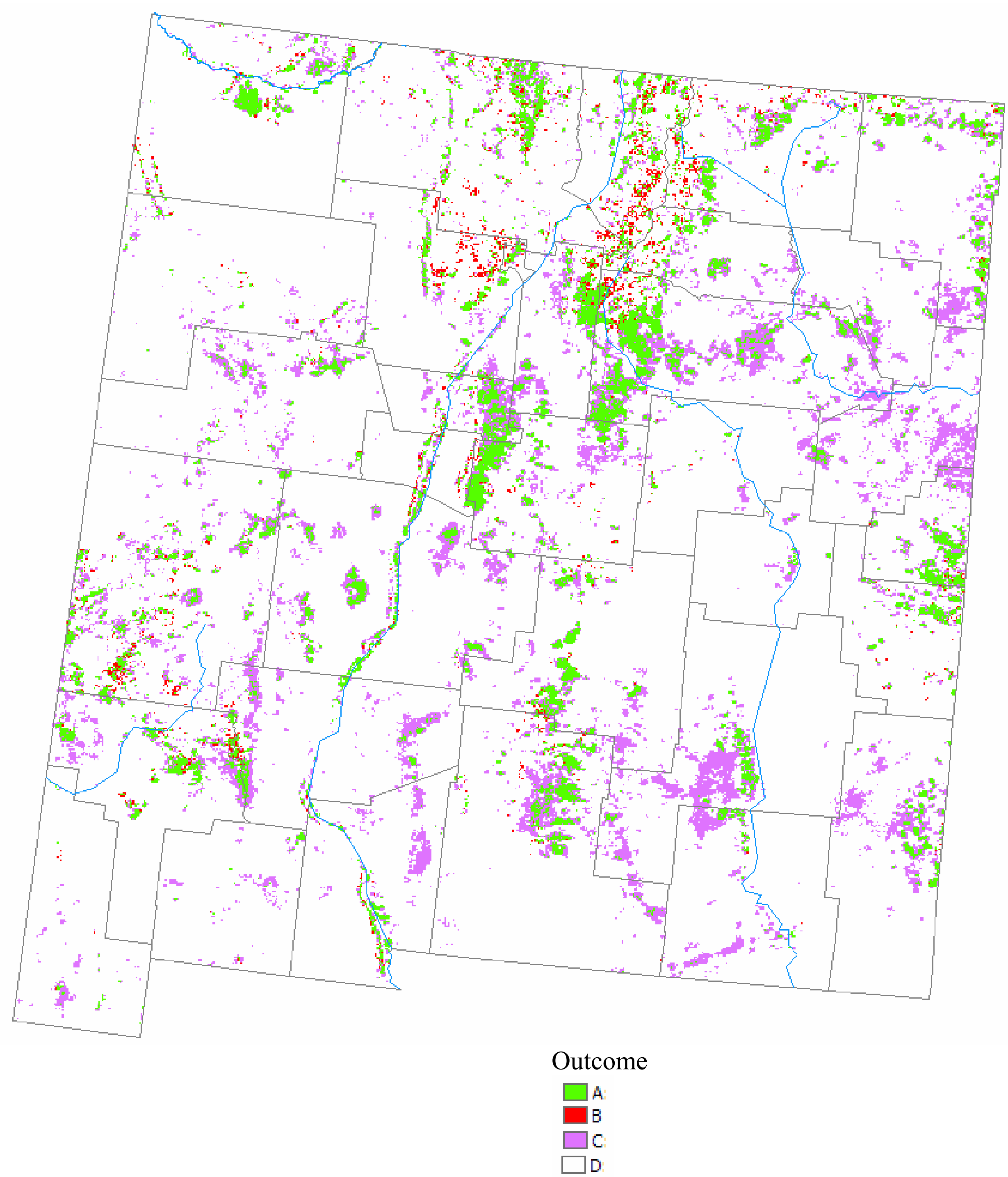


Fig. S4. Comparisons of the NDVI trend significance between the univariate and multivariate autoregression analyses for each pixel. Outcomes (A-D) are defined in Table 2.

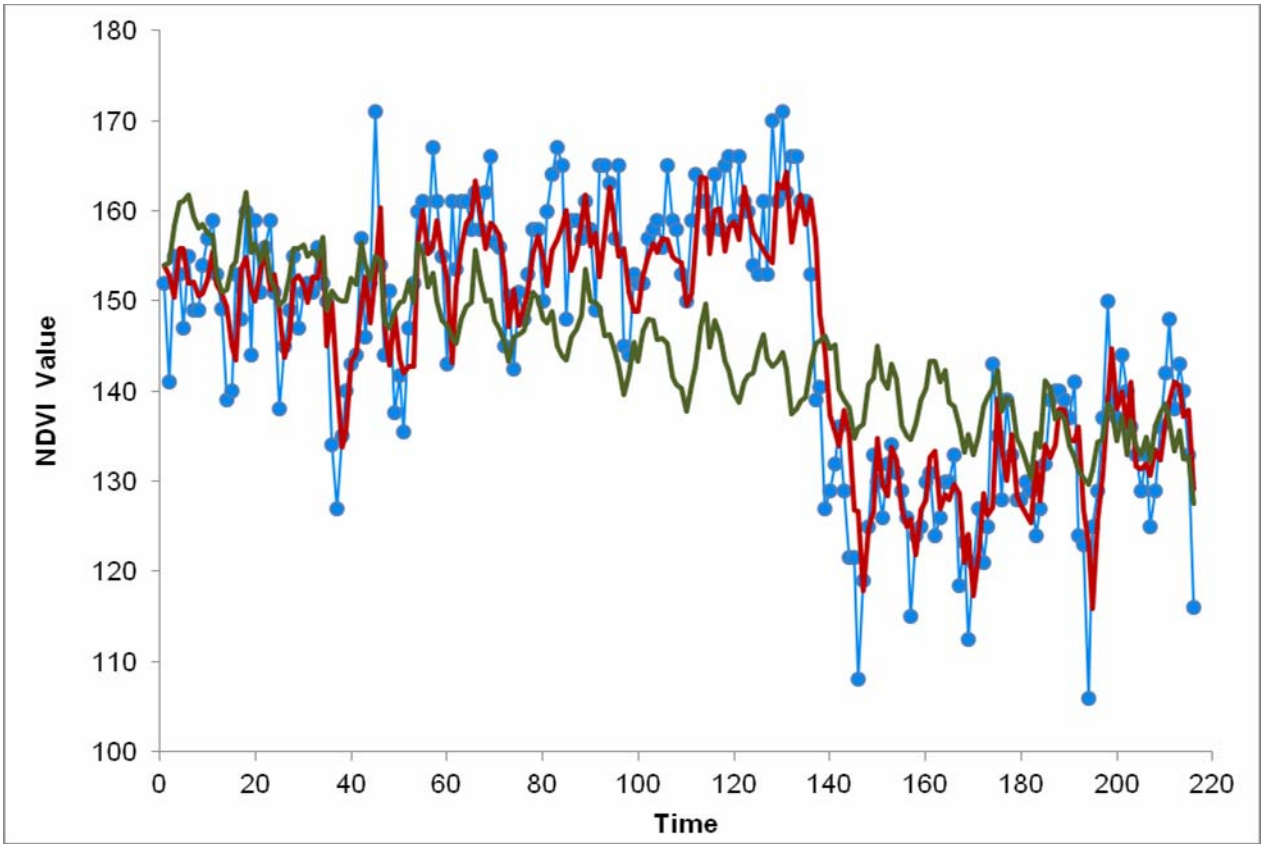


Fig. S5. Observed and predicted values for NDVI for one pixel in the Cerro Grande Fire (pixel A in Fig. 6). The blue line connects the observed values (blue closed circles, n=216). The fitted multivariate autoregression model (i.e., predicted NDVI; red line) and the green line represent the structural part of the multivariate autoregression model (see explanation for Equation 2*a*). NDVI trend with time ($\beta_6 = -0.118$) is significant ($p = 0.022$).

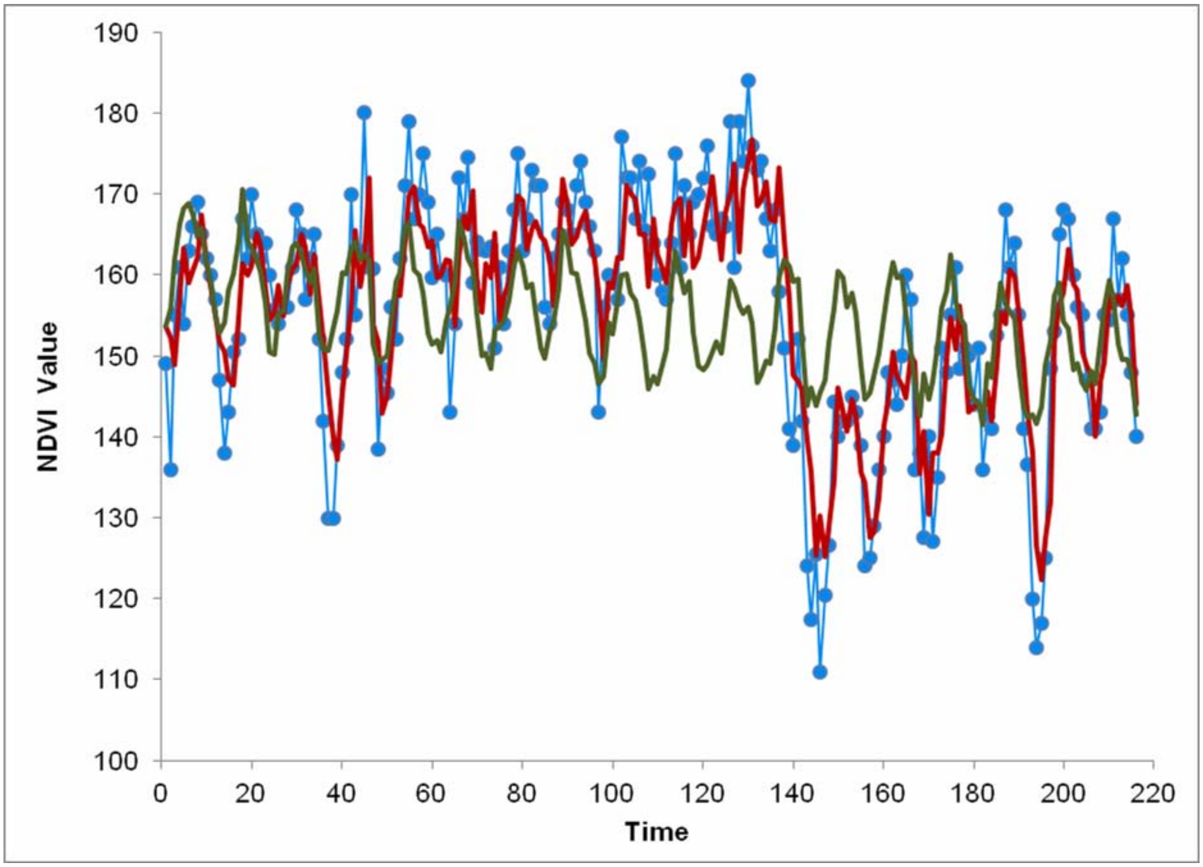


Fig. S6. Observed and predicted values for NDVI for one pixel in the Cerro Grande Fire (pixel B in Fig. 6). NDVI trend with time ($\beta_6$ = -0.061) is not significant (p = 0.336). Lines and symbols are described in Fig. S5.