# 3A.3 METHODS FOR EVALUATING SPATIAL SEASONAL FIRE POTENTIAL INDICES

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## 1. INTRODUCTION

Several spatial products are available for tracking changes in fire potential (fire danger) and more are under development. Such indices are developed from satellite data and gridded weather models. Evaluating a spatial fire potential product is the process of comparing fire occurrence and size data with a map of fire potential values. Methods of evaluation developed to date have included both model and non-model-based techniques, but few have attempted to explicitly account for the spatial and temporal correlation present among the fire potential readings and the fire history observations. We present the use of a randomization method, a percentile method, and a four-dimensional median polish trend removal technique. For each of these methods, we also address the issue of spatial scale by considering multiple spatial resolutions of the data. We demonstrate these methods developed in "R" for AVHRR NDVI-derived Relative Greenness (RG) and Departure from Average (DA) for Washington and Oregon. Through results from one section of the study site, we highlight both the simplicity of our methods and the interpretability of our results. Overall, we found few differences between RG and DA with the exception of a few small areas in the study site. Both RG and DA seem to be indicators for large fires in most areas, but are not indicators of small, lightning, or human-caused fires.

## 2. BACKGROUND

Evaluating a fire potential product is generally the process of comparing such a product with historical fire observations, assessing the strength of the relationship between the two. The products we evaluate here are constructed using the Normalized Difference Vegetation Index (NDVI) (Burgan and Hartford 1993). Although we will only be working with data from the states of Oregon and Washington, we aim to find methods that will allow us to assess any fire potential product over any given area.

In order to evaluate the information provided by a fire potential product, we need to quantify the relationship between the product and fire ignition. Logistic regression models have previously been used to model the probability of a fire ignition based on a fire danger index (Perestrello 2001, Loftsgaarden and Andrews 1992, and Andrews et al. 2003). However, very few models have attempted to account for the spatial and temporal correlation among observations. Preisler et al. (2004) used a conditional probability model to estimate the risk of large fires using fire indices and weather variables. This model incorporated both a temporal and spatial variable to model the probability of a large fire occurrence, given that a fire was ignited in that area. Peng et al. (2005) employed a space-time conditional intensity model to assess Burning Index (BI) for Los Angeles County.

Graham et al. (2006) used two non-model based tools, accounting for the spatial and temporal association between observations, to assess the relationship between fire indices and fire ignition for an area in northwestern Nevada. A randomization method comparing fire indices at fire and non-fire locations was used to test for an association between fire ignition and fire indices at different spatial resolutions. In addition, a separate method involving a partial Mantel correlation statistic was also investigated. The partial Mantel statistic is very similar to Pearson's correlation coefficient, but measures the association between distance matrices after accounting for the spatio-temporal correlation present.

## 3. DATA

### 3.1 *Fire Data*

Between May and October from 1994 to 2006, there were 48,812 fires ignited in Oregon and Washington. These fire ignition sites are displayed below in Figure 1. In addition to the location of the initial ignitions, the cause of ignition and total acres burned

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were also recorded. These data were obtained from the Northwest Geographic Area Predictive Services GIS Coordinator.

*Figure 1: Locations of all observed fire ignitions in Oregon and Washington taking place between May and October (1994 to 2006).*

**3.2 *Fire Potential Products***

Using The National Oceanic and Atmospheric Administration's (NOAA) weather satellites, data are gathered by the Advanced Very High Resolution Radiometer (AVHRR) from which the Normalized Difference Vegetation Index (NDVI) is formed. The NDVI images consist of 1.1-kilometer square pixels, displaying the normalized difference between the near-infrared and visible red reflectance values (Burgan and Hartford 1993). These values range from -1 to 1 where -1 implies either cloud cover, snow cover or water, and 1 implies dense green vegetation. Daily images are combined into weekly composites, where for each pixel, the highest NDVI value among the seven days is used for that week. Furthermore, each weekly NDVI image is combined in the same way with the NDVI image from the previous week. These weekly data have been recorded since 1989 and are readily available to the public at (http://www.wfas.net).

Although the NDVI data are measured amounts of vegetation for a pixel, they must be compared to historical vegetation readings to be useful fire potential indicators. Considering a particular pixel in a given area, we define the following:

- $NDVI_p$ = *Observed NDVI value for present week for that pixel*
- $NDVI_{mx}$ = maximum NDVI value since 1989 for that pixel
- $NDVI_{mn}$ = minimum NDVI value since 1989 for that pixel
- $NDVI_{ave}$ = average NDVI value since 1989 for that pixel for the given week.

$$RG = \frac{NDVI_p - NDVI_{mn}}{NDVI_{mx} - NDVI_{mn}} * 100 \qquad (1)$$

$$DA = 100 + (NDVI_p - NDVI_{ave}) * 100 \qquad (2)$$

Relative Greenness (RG), defined in (1), is a percentage measuring the greenness (NDVI) for that pixel relative to all other fire seasons since 1989 (Burgan and Hartford 1993). RG values range from 0 to 100 and those closer to 100 indicate that a pixel has a large amount of vegetation relative to past years since1989.

Departure from Average (DA), defined in (2), is a function of the difference between the present and average NDVI values at each pixel. DA values range from 0 to 200 where values closer to 200 indicate that a site has much more vegetation than usual and values close to 100 indicate that a site is close to the average NDVI for the past fire seasons since 1989.

DA and RG both provide a measure of vegetation for a particular site relative to how vegetated that site has been in the past. Both indices attempt to show us abnormalities occurring in the landscape during a specific time. Areas with low RG or DA values will be dryer than usual, possibly indicating more suitable conditions for fire ignition.

For this study we consider weekly DA and RG images from 2001 through 2003 taken from Oregon and Washington. Each weekly image is processed as a 742x870 rectangular lattice. We attempt to evaluate these indices in the next section by comparing them with fire history observations.

**3.3** ***Predictive Service Areas***

While we would ideally like to find a fire danger index that is superior for all vegetation types and all landscapes, we acknowledge that some indices may perform better in certain areas than others. For this current study, we have broken up our study site into the twelve predictive service areas defined by Northwest Geographic Area Predictive Services meteorologists (Figure 2). We included boundaries into our study with the idea that different types of layers could later be incorporated into our analysis program such as elevation or vegetation type.

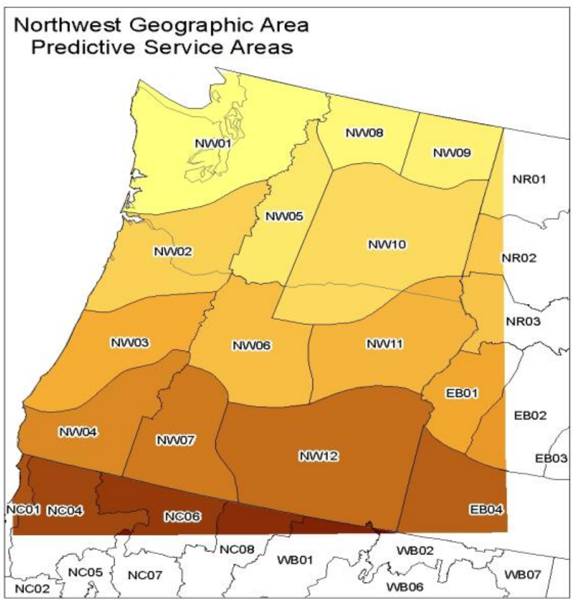


*Figure 2: Predictive Service Areas for Oregon and Washington.*

## 4. METHODS AND RESULTS

The goal of this project is to develop and test a set of analysis tools that will allow a user to compare how well two or more fire potential indices are related to fire history observations. These methods are currently being developed and tested using the free statistical software R. R provides users with the ability to visualize data effectively, utilize many analysis methods, and develop new methods specific to a given problem. These combined features of R provide us with a good environment for experimenting with and testing new analysis techniques.

Because some areas are more prone to higher acreage fires than others, we allow for flexibility in these size thresholds. We can define size thresholds relative to the rest of the area while using any of the methods described below. The analysis techniques are illustrated here using 15 acres as a size threshold. This was used because it is the 95$^{th}$ percentile of all fire sizes for fires ignited in predictive service area 11.

**4.1** ***Exploratory Data Analysis***

Visualizing both the fire data and the fire potential indices is an important step in the assessment process. We have incorporated several techniques into our analysis program to allow for the initial exploration of the indices. Shown in Figure 3 is an example of one such visual technique. This figure displays the weekly mean and median RG values for 2003 compared to the number of fires ignited in that week.

This plot allows us to see any overall associations between the weekly number of ignitions and the weekly average or median index value. Figure 3 does not show any association between RG and fire ignitions. If an association were apparent, we would expect to see lower RG values corresponding with a higher number of fire ignitions. However further analyses taking into account spatial locations of the fire ignitions and fire potential indices may still provide further information.

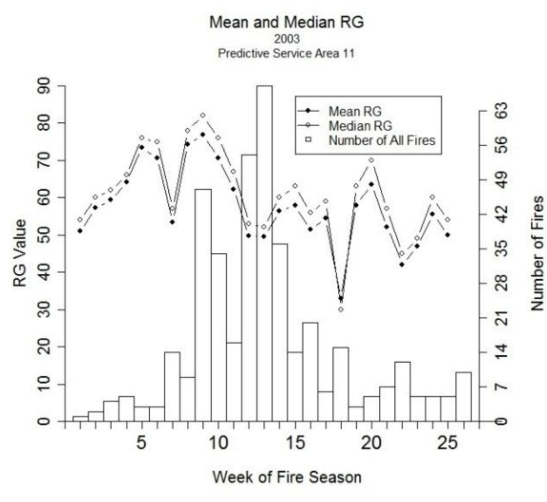


*Figure 3: Weekly mean and median RG values plotted over the number of weekly fire ignitions for Predictive Service area 11.*

### 4.2 ***Spatial Scale***

Fire danger indices are recorded at specific spatial resolutions. For example the data presented here are recorded on a one square kilometer resolution. However, some fire potential products may provide the same or better fire danger information at a lower resolution. We investigate this possibility by analyzing the relationship between fire history and the fire indices at multiple spatial resolutions.

While efforts are made to minimize error in both the fire potential indices and the fire locations, there are still errors in the data. Some fire potential readings are actually representing cloud cover, some fire ignitions are never recorded, and other fire ignition locations are recorded incorrectly. It may be that considering data at a different spatial scale will appropriately represent the data in the manner they were recorded. Figure 4 shows RG reduced in resolution from $1km^2$ to $2km^2$ while Figure 5 shows a DA image from the week of August $3^{rd}$, 2000 reduced in resolution from $1km^2$ to $12km^2$.

The three analysis methods discussed in the next sections can all be explored at multiple spatial resolutions.

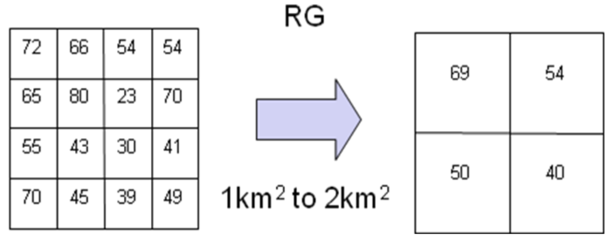


*Figure 4: Reducing the resolution of RG from $1km^2$ to $2km^2$ using the median.*

### 4.3 ***Percentile Method***

This method simply compares the distribution of fire potential indices for fire sites to that for sites without an observed fire. If a fire index is a good fire danger indicator, then higher or lower index values should indicate sites having a greater risk of fire (depending on the fire index). For RG and DA, we would expect lower index values to be associated with higher fire danger. It would therefore be reasonable to expect sites with an observed fire to not exceed the $75^{th}$ percentile of all fire index values.

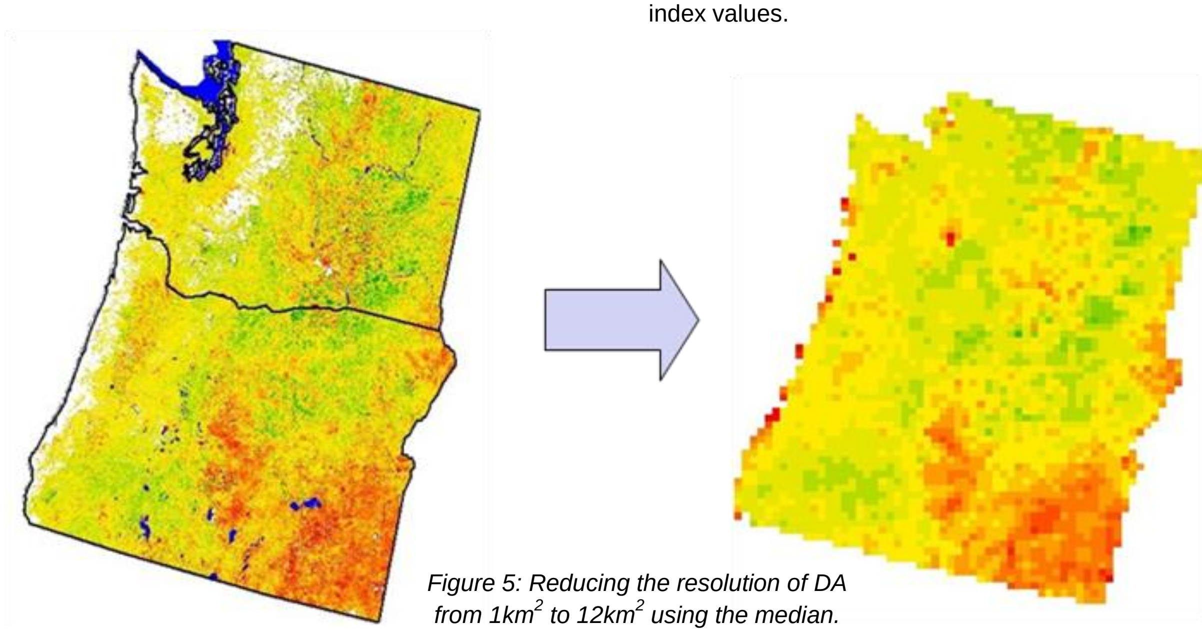

*Figure 5: Reducing the resolution of DA from $1km^2$ to $12km^2$ using the median.*

Displayed below in Figure 6 is an illustration of this idea. The shaded area in the upper tail of the distribution for fire sites represents the proportion reported from this method. Proportions smaller than 25% may indicate the index is providing some fire danger information for that given area. Results from this method for predictive service area 11 are shown in Figures 7 and 8. It can be seen in these plots that both RG and DA seem to be decent indicators for large fires with a low proportion of large fire sites exceeding the 75$^{th}$ percentile. However, they do not seem to be indicators of human-caused fires. Also apparent in these plots is that the proportions change very little as the spatial scale decreases.

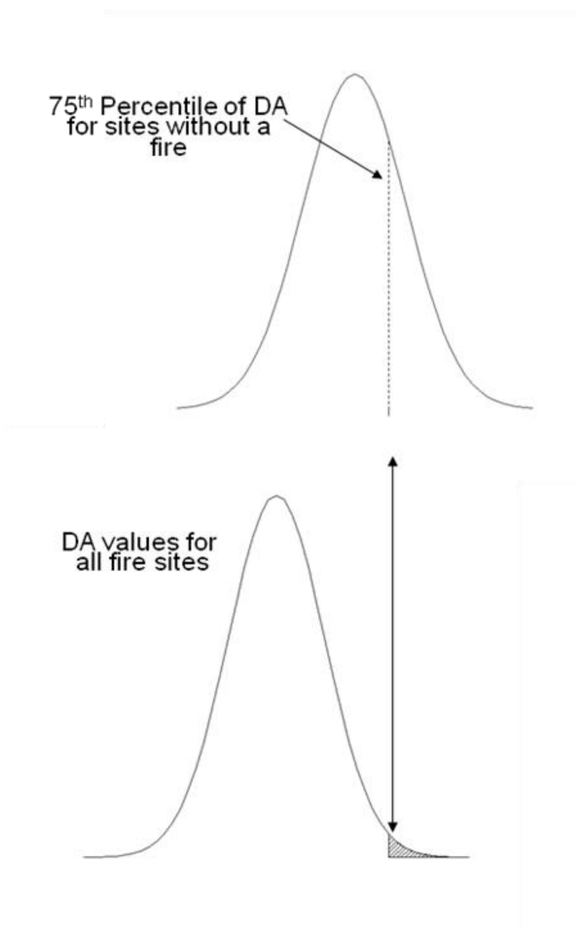


*Figure 6: Illustration of percentile method: comparing the distribution of DA values for all sites to the distribution of DA values for only fire sites.*

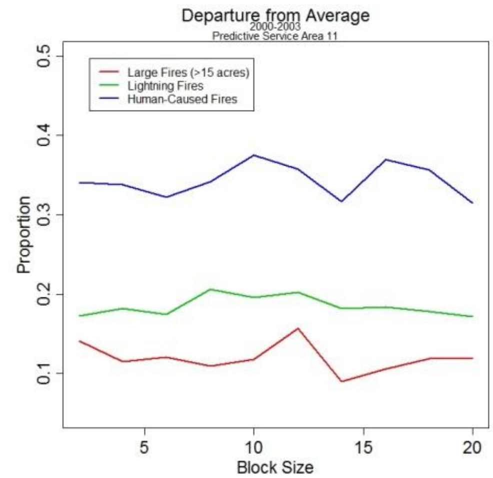


*Figure 7: Results from the percentile method for Departure from Average over multiple spatial scales: Predictive Service Area 11.*

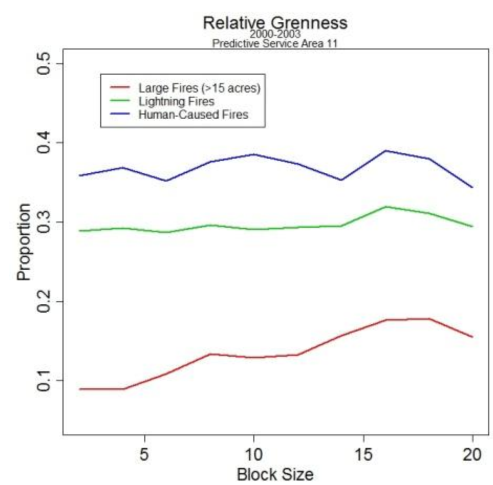


*Figure 8: Results from the percentile method for Relative Greenness over multiple spatial scales: Predictive Service Area 11.*

### 4.4 *Random Points Method*

The random points method is a significance test allowing us to assess whether sites with an observed fire ignition have a significantly lower mean fire potential index than would be expected if those fires simply occurred randomly. Graham et al. (2006) used this method as an initial exploration method for detecting any relationship between fire ignition and fire potential indices. Letting *n* represent the number of observed fires, randomization p-values are obtained by repeatedly (in this case, m=499) randomly sampling *n* sites and computing their mean index value. Figure 9 shows that sites having a fire over 15 acres had significantly lower mean RG and DA values than the other sites. In addition, these significance values did not start to change until reaching a spatial resolution of $12km^2$. This might suggest that the fire potential indices are performing similarly at a lower spatial resolution. Figure 10 displays these same types of significance values, but calculated weekly over the fire season. This type of analysis allows us to study how an index performs throughout the fire season. In this figure, we see that RG seems to be the most reliable for large fires, especially during the height of the fire season when the number of large fires reached 45.

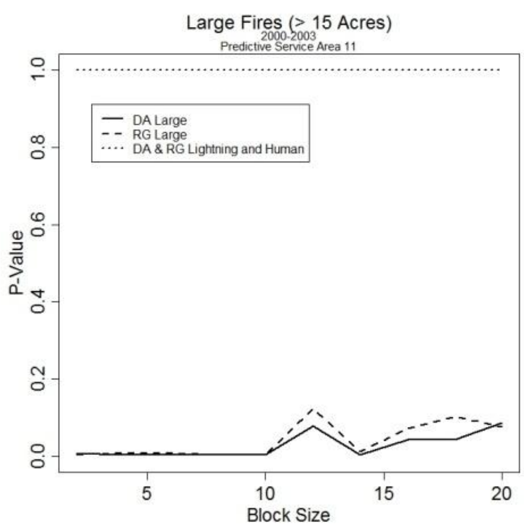


*Figure 9: Results from the random points method comparing RG and DA over multiple spatial scales: Predictive Service Area 11.*

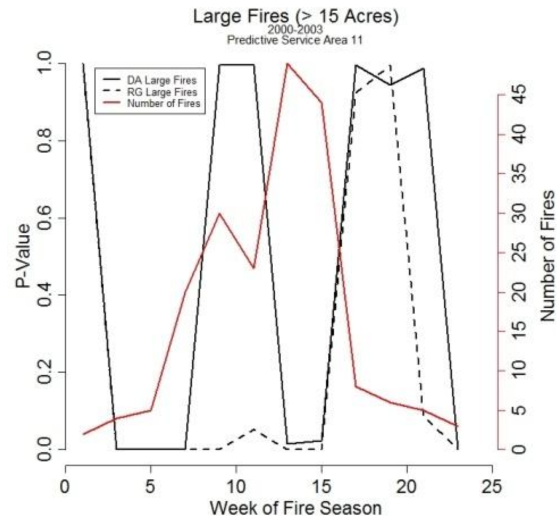


*Figure 10: Results from the random points method comparing RG and DA over time at a 2km resolution : Predictive Service Area 11.*

### 4.5 *Median Polish*

We use the Median Polish method for two reasons. 1) It is a nice exploratory analysis tool for gridded data. 2) It allows us to remove spatial trend present in the data so we may perform statistical analyses on the remaining residuals.

The Median Polish (Bailey and Gatrel 2006) is an algorithm which repeatedly removes column, row, week, and year medians until each dimension has a median of 0. While the Median Polish is traditionally performed on two-dimensional lattice data, we have extended the method to partition the fire index data into six parts: main effect, column effects, row effects, week effects, year effects, and the remaining residuals (see (3) below).

$$\boxed{\text{Fire Index} = \text{Main} + \text{Row} + \text{Column} + \text{Week} + \text{Year} + \text{Residual}} \quad (3)$$

The resulting effects can be thought of as large scale trends present in the data. A negative column effect indicates that column has lower than normal index values compared to other columns in the lattice. Shown below in Figures 11 and 12 are the column and week effects from the four-dimensional median polish of RG for predictive service area 11. Figure 11 shows the tendency for smaller column effects to be associated with more fires. Figure 12, however, does not show any clear association between weekly effects and the number of weekly fires.

We are currently incorporating methods into our analysis that will assess the relationship between the residuals from the median polish method and fire history.

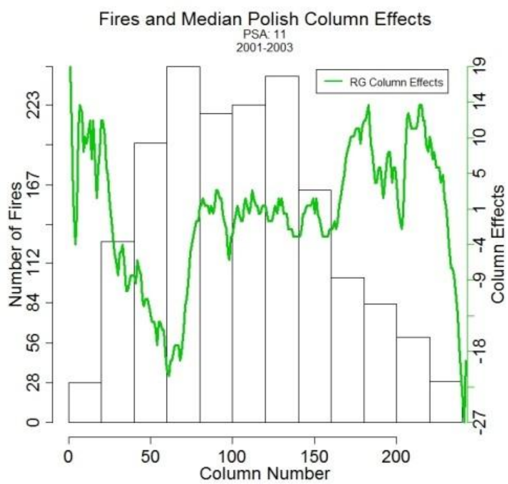


*Figure 11: Column effects from the Median Polish Trend Removal for Predictive Service Area 11.*

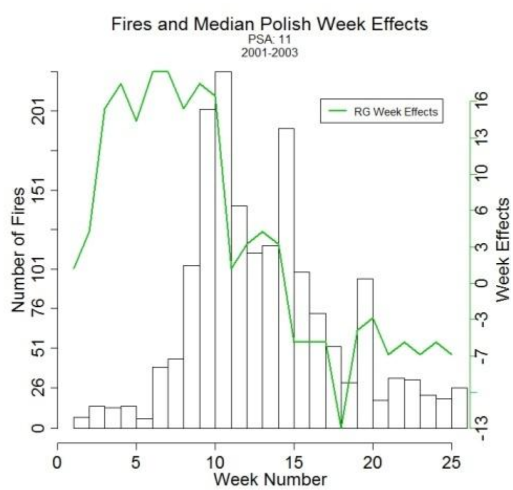


*Figure 12: Week effects from the Median Polish Trend Removal for Predictive Service Area 11.*

**5. CONCLUSIONS AND FUTURE WORK**

In general, across all predictive service areas, we have found very few differences between RG and DA based on their association with fire history. Both RG and DA were found to be potential fire danger indicators for large fires, but were usually not strongly associated with human-caused or lightning fires. Spatial resolution was not found to be a significant factor when assessing the relationship between fire potential indices and fire history. In other words, in most cases we did not find any more information from an index at a 1 $km^2$ scale than we did at a 10 $km^2$ scale.

While very simplistic, the percentile and random points methods are very informative and easily interpretable. Future methods we incorporate will assess the relationship between the median polish residuals and fire ignition. This will be an alternative to the Partial Mantel Test carried out by Graham et al. (2006) discussed earlier.

This study has only assessed the relationship between AVHRR NDVI-derived RG and DA. We are currently working on incorporating two more indices into our study: MODIS EVI-derived RG and DA.

These methods provide a framework to assess the relationship between any spatial dataset and fire occurrence. Ultimately, this will assist researchers and land managers in identifying the spatial fire potential indicators that are the most closely related to fire activity. These indicators will help managers make more informed fire management decisions.

**6. ACKNOWLEDGEMENTS**


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**7. REFERENCES**


Andrews, P.L., Loftsgaarden, D.O., and Bradshaw, L.,2003: Evaluation of fire danger rating indexes using logistic regression and percentile analysis, *International Journal of Wildland Fire*,**12**, 213-226.

Bailey, T.C., and Gatrell, A.C.. 1995. Interactive Spatial Data Analysis. Prentice Hall, Pearson Education Limited, England.

Burgan, R.E. and Hartford, R.A.,1993: Monitoring Vegetation Greenness with Satellite Data, GTR-INT-297, USDA Forest Service, Ogden, UT.

Graham, J.M., Andrews, P.L., and Jolly, W.M., 2006: The Use of a Mantel Correlation Statistic for Assessing Wildfire Potential Indicators. *In D.X. Viegas (Ed.) 2006. Fifth International Conference on Forest Fire Research.*

Loftsgarden, D.O., and Andrews, P.L. (1992), Constructing and Testing Logistic Regression Models for Binary Data: Applications to the National Fire Danger Rating System, *USDA Forest Service, Intermountain Research Station Technical Report,* INT-286.

Peng, R.D., Schoenberg, F.P., Woods, J.A., 2005:, A space-time conditional intensity model for evaluating a wildfire hazard index, Journal of the American Statistical Association,**100(469)**, 26-35.

Perestrello, M.J., Silva, S., Tom, M., Alvim, M., Cardoso Pereira, J.M.,2001: Spatial Prediction of Fire Ignition Probabilities: Comparing Logistic Regression and Neural Networks*, Photogrammetric Engineering and Remote Sensing, **100(469)**, 26-35.*

Preisler, J.K., Brillinger, D.R., Burgan, R.E., and Benoit, J.W. ,2004: Probability Based Models for Estimation of Wildfire Risk, *International Journal of Wildland Fire,* **13**, 133-142.