USING IN-SITU OBSERVATIONS BY WILDLAND FIRE FIGHTERS TO ASSESS DETECTION BY MODIS

A Thesis

Presented in Partial Fulfillment of the Requirements for the

Degree of Master of Science

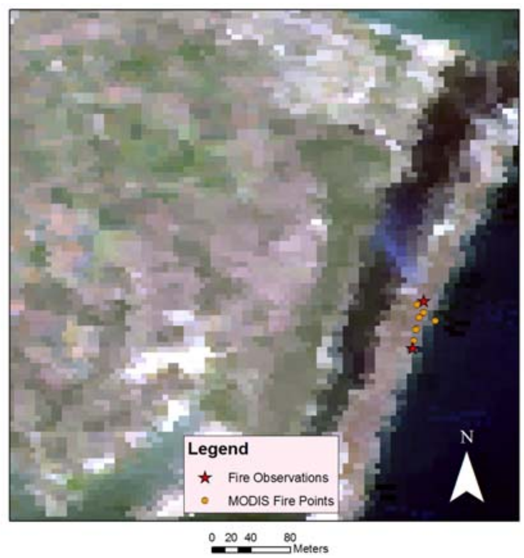
with a

Major in Forest Resources

in the

College of Graduate Studies

University of Idaho



By

Heather Levina Heward

May 2009

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Major Professor ________________________________ Date ____________

Penelope Morgan

Committee

Members ________________________________ Date ____________

Alistair M.S. Smith

________________________________ Date ____________

Jeff A. Hicke

Department

Administrator ________________________________ Date ____________

Jo Ellen Force

Discipline's

College Dean ________________________________ Date ____________

Bill J. Mclaughlin

Final Approval and Acceptance by the College of Graduate Studies

________________________________ Date ____________

ABSTRACT

The MODIS active-fire product is currently being used by fire researchers and fire managers to monitor the occurrence, extent, and other characteristics of fire nationally and globally. The goal of this study was to evaluate how *sensor zenith angle*, *flame length*, *area burning*, *rate of spread*, *fire movement*, *fire activity*, *canopy cover*, and *ecoregion class* affect the detection of active fire with the MODIS active-fire product. A total of 265 active-fire observations were taken in 13 states by wildland fire fighters during the summers of 2007 and 2008; 12% were taken in grasslands, 15% in shrublands, and 73% in forests. Of these observations, 34% were detected by MODIS. *Sensor zenith angle* and *fire activity* had the greatest influence on the detection of fire, with the detection rates ranging from 56% for a *sensor zenith angle* of 0 to 10 degrees to 12% at a *sensor zenith angle* of 60 to 70 degrees, and detection rates for *fire activity* ranging from 56% for a fire with torching to 5% for a creeping fire. Observations with the lowest *sensor zenith angle* and the highest *fire activity* were detected 66% of the time. Through several case studies of fires that were observed but not detected, cloud cover and missing data were found to be possible contributors and may account for some of the differences between observed and detected fire activity.

ACKNOWLEDGEMENTS

Funding for this project came from the University of Idaho and partly from the Joint Fire Sciences Program award # 07-2-1-60. I would like to thank Brad Quayle from RSAC for his assistance in gathering and understanding the MODIS data available on the RSAC website; his willingness to provide extra data processing and reference material was instrumental to the completion of this project. In addition to Penny Morgan, Alistair Smith and Jeff Hicke, Chad Hoffman, Zach Holden and Marshell Moy assisted in the development and implementation of the methods used in this study. Chad Hoffman and Francisco Rego provided essential guidance on data analysis and statistical methods. I am grateful to all of the participating fire crews for the valuable data they collected; Kings Peak FUM module in particular, specifically Charity Parks, collected a great deal of quality fire observations during both the summers of 2007 and 2008. Special thank you to the Bandelier FUM for allowing me to collect data while a member of their crew. This project would also not have been possible without the support of Michel Heward and Mark and Meredith Thibo.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

APPENDIX

INTRODUCTION

Background

Monitoring the location, size, growth and intensity of large fires is a high priority for both fire scientists and fire managers in the US and abroad. On a global scale it is becoming increasingly important to understand the contributions that fires make to changes in the composition of the atmosphere. A large percentage of the global emissions of greenhouse gasses are produced by burning biomass (Penner *et al.*, 1992, IPCC 2007), and these gases have a significant effect on the atmospheric chemistry, cloud properties and radiation budget (Crutzen *et al.*1979; Crutzen and Andreae 1990; Kaufman *et al.*1992; Kaufman *et al.*1998*a*). In the United States, with 10 to 12 million acres (4 to 4.8 million ha) expected to burn annually (QFR 2009), costs increasing to as much as $220 per acre ($553 per ha)(www.nifc.gov, QFR 2009), and a rapidly growing wildland urban interface (Theobald and Romme 2007), fire managers need ways to quickly, reliably and accurately detect where fires are burning and how intensely.

Satellites have been used to observe fires on a global scale, providing a variety data products with differing spatial, spectral, and temporal resolutions. Fire occurrence can be monitored by either detecting changes on the ground or detecting active burning. Several sensors that are commonly used to identify and analyze burned areas are Advanced Very High Resolution Radiometer (AVHRR) (Flannigan and Vonder Haar 1986; Kaufman *et al.*1990), SPOT VEGETATION (Stroppiana *et al.*2002; Silva 2003 *et al.*2003), and Landsat (Salvador *et al.*2000; Holden *et al.*2005). Pre- to post-fire change in vegetation inferred from satellite imagery is commonly used to assess fire effects, such as burn severity (Rouse *et al.*1974; Wilson and Sander 2002; Key and Benson 2005; Lentile *et al.* 2006). Sensors developed for observing actively burning fires include the Moderate Resolution Imaging Spectroradiometer (MODIS) (Justice *et al.*2002; Wooster *et al.*2003; Smith and Wooster 2005), Advanced Very High Resolution radiometer (AVHRR) (Frazer *et al.*2000; Kennedy *et al.*1994), the Along Track Scanning Radiometer (ATSR) (Eva and Lambin 1998) and others (Riggan *et al.*2004; Butler *et al.*2004).

MODIS is commonly used by fire mangers in the US to get general information about fire activity across the country and to monitor local fire occurrence and activity (http://activefiremaps.fs.fed.us/; www.geomac.gov/). This information has proved useful in the organization of large incidents by indicating the locations of actively burning fires, , in visualizing direction of growth for remote fires that are not frequently monitored by other means, and occasionally to identify new fires. Although fire managers increasingly depend on fire perimeter and location information inferred from MODIS imagery, the degree to which fires are reliably detected with MODIS and the factors affecting detection have not been widely tested with on-the-ground fire observations.

Detection of active fires using MODIS

In this study, I compare the MODIS active-fire product (i.e. MOD14) to *in-situ* data collected by fire observers. I use MODIS because of its advanced fire detection algorithms (Giglio *et al.* 2003; Csiszar *et al.* 2006; Hawbaker *et al.* 2008), the availability of MODIS imagery for most locations several times daily, and the frequent use of MODIS imagery by fire managers and fire scienctits. MODIS was first launched on the Terra platform in 1999 and then on the Aqua platform in 2002 (Justice *et al.* 2002). MODIS has a spectral resolution of 250 m in the red and near-infrared which is aggregated to reduce false detections and clouds (Giglio *et al.* 2003) producing a final resolution of 1 km with a sub-pixel accuracy of 50 m at nadir (Wolf *et al.* 2002). Images are available from MODIS 3 to 4 times a day on average; from Terra at around 5:30 and 18:30 Greenwich Mean Time (GMT), and from Aqua at around 9:30 and 20:30 GMT (http://www-air.larc.nasa.gov/tools/predict.htm), with times varying as much as an hour from day to day at any given location.

Of the wavelengths of the electromagnetic spectrum observed using MODIS, the information collected by the 4μm (T_4) and 11μm (T_{11}) wavelengths (Kaufman *et al.*1998*a*; Giglio 2003; Justice *et al.* 2006) provides a distinct signal of fire by taking advantage of the large amount of mid-infrared radiation being emitted (Dozier 1981; Matson and Dozier 1981). The two 4μm channels of MODIS are 21 and 22 which saturate at nearly 500 K and 331 K respectively. Channel 22 is less noisy and used whenever possible, but if the temperature of the pixel exceeds 331 K, channel 21 is used to derive T_4 (Giglio *et al.* 2003). The information for T_{11} is collected from Channel 31; it saturates at 400 K for Terra and 340 K for Aqua (Giglio *et al.* 2003).

The fire detection algorithm is designed to detect as much active burning as possible with the fewest false detections. MODIS does not have on-board calibration, which has necessitated a series of adjustments (Giglio *et al.* 2003; Justice *et al.* 2006) to the original detection algorithm from the prelaunch calibration (Kaufman *et al.* 1998*a*). Analysts systematically classify each pixel as either fire, missing data, cloud, water, non-fire, or unknown. The first pixels to be removed from the pool of possible fires are those with missing data, followed by those that have been classified as cloud or water (Giglio *et al.* 2003). All remaining pixels are processed and flagged as potential fire if they pass the following criteria: T_4>310 K (305 K at night), ΔT>10 K (where $\Delta T = T_4 - T_{11}$), and when channel 2 which is used to identify sunglint is <0.3 (omitted at night) (Giglio *et al.* 2003). Of the pixels that pass this criteria, those that have a T_4 of >360 K (320 K at night) are considered to be unambiguous fire, while all others move on to a second round of screening.

The background around each pixel is used to estimate what the radiometric signal would be without the presence of fire (Giglio *et al.* 2003). This is done by selecting a window around the pixel, starting at 3 X 3 pixels, and increasing the size of that window up to 21 X 21 pixels until at least 25% or 8 of the neighboring pixels are deemed valid. In this process, there is a distinction made between those background pixels that have also been classified as potential fire, and those that have not. After background characterization is complete to the standards specified, a series of contextual tests are performed to isolate the fire pixels, reject small convective cloud pixels, and account for the possible interference from windows that contain large fires (Giglio *et al.* 2003). Pixels that fail contextual tests are labeled as no-fire or unknown. Potential sources of false detections accounted for in the algorithm include sunglint rejection, desert boundary rejection, and coastal false alarm rejection (Giglio *et al.* 2003).

Kaufman *et al.* (1998*b*) introduced the concept of remotely measured fire radiative energy (FRE) to improve the detection of active fires. FRE can be inferred directly from Earth-orbiting satellites since it is a measure of the chemical energy emitted from burning vegetation as radiation (Wooster *et al.*2003). Kaufman *et al.* (1998*b*) found the calculation of FRE to improve the detection of active fires, and Wooster (2002) found FRE valuable for assessing biomass combustion in natural wildfires (Wooster *et al.*2003). FRE is a measure over the whole area of the fire, while fire radiative power (FRP) is a measurement of the energy of fire at the pixel level; FRP is directly related to the rate of fuel combustion (Kaufman *et al.*1998*b*; Wooster *et al.*2003). Smith and Wooster (2005) found an order of magnitude difference in the FRP from head fires and back fires which is consistent with field measures of fire-line intensity (FLI) (Trollope *et al.*1996; Lentile *et al.*2006).

MODIS product validation

In order to correctly interpret satellite-based fire detection data and avoid misunderstandings about data quality (Csiszar *et al.*2006), validation of these sensors should be performed to reveal the product accuracy in a variety of environmental situations. The importance of validation has prompted the development (Morisette *et al.*2002) and implementation (Morisette *et al.*2005a, Morisette *et al.*2005b, Csiszar *et al.*2006) of a framework for determining the accuracy of the MODIS active-fire product (Table 1). There have also been validation studies performed that do not follow this framework but provide valuable information on active fire detection (Cardosa *et al.*2005, Hawbaker *et al.*2008) or look specifically at the FRE (Wooster *et al.*2003,) or FRP (Mottram *et al.*2005, Smith and Wooster 2005).

Although some validation has been performed on the MODIS active-fire product, the increasing demand for remotely sensed active fire necessitates a better understanding of this and other products (Schroeder *et al.* 2008). Validation studies that have taken place to date typically use higher spatial resolution sensors for comparison, most commonly ASTER (Table 1). In an effort to avoid some of the compounding errors and limitations of using other sensors for validation, I use *in-situ* data collected by wildland fire fighters, primarily during the summers of 2007 and 2008. Unlike validation using ASTER, my method allows fires that are viewed at angles higher than 8.5˚ to be checked for detection. Although these *in-situ* data are not temporally coincident (a great benefit to using ASTER) (Morisette *et al.* 2005a, Morisette *et al.* 2005b, Csiszar *et al.* 2006), my study demonstrates whether or not fire behavior in a small window of time can be inferred using MODIS. Having active fire observations taken from the ground also provides an opportunity to identify and evaluate some of the variables that may influence fire detection. Both sensor-to-sensor and *in-situ*-to-sensor validation are important to using and understanding the MODIS active-fire product for many different applications across continents.

Objectives

The objectives of this study are to:

a. Use wildland fire fighters to effectively collect quality on-the-ground data on active fire behavior that can be compared to observations from satellites.
b. Evaluate the variables that influence fire detection with MODIS.
c. Identify the likelihood of fire detection with MODIS at thresholds for each of the variables.

d. Identify the relationship between FRP and the active-fire observations.

I hypothesize that:

a. Of the groups asked to collect data, 20% will return usable observations; variability in fire season and individual fire assignments will account for this low rate of return
b. Variables that will influence the detection of fire using MODIS will be *sensor zenith angle*, *flame length*, *area burning*, *rate of spread*, *fire movement*, *fire activity*, *canopy cover*, and *ecoregion class*.
c. As *sensor zenith angle* and *canopy cover* decrease and *flame length*, *area burning*, *rate of spread*, *fire movement* and *fire activity* increase, the probability of fire detection using MODIS will increase.
d. FRP and the fire activity level are positively correlated

METHODS

Fire observers

Almost all actively burning wildland fires in the United States are staffed with fire personnel performing monitoring, suppression, resource protection or other fire management activities. There are very strict safety regulations regarding the qualifications required to work near actively burning fires; these regulations often make it difficult for research teams to enter into a fire area during active burning.

To take advantage of the resources that are already in the position to monitor fires, I used Fire Use Modules (FUMs) and Interagency Hotshot Crews (IHCs) to take active-fire observations. FUMs each include 7 to 11 people, most of whom are qualified Fire Effects Monitors (a government qualification signifying that the person has taken the course work for and had practice in observing fire behavior and effects). Although these crews participate in a variety of activities on fires, their typical role is backcountry observation and tactical operations. During the summer months, FUMs are commonly assigned to wildfires that are being managed to burn with little or no human intervention. Outside of the wildfire season, FUMs are often used to implement prescribed burns. FUMs observe fire activity and weather, and they work to protect certain resources threatened by fire. The location and function of these crews make them ideal for collecting a few points of additional information in their current active-fire observations.

Interagency Hotshot Crews each include 20 to 22 individuals. They often work close to the major fire activity in their serious and sometimes dangerous job of fire suppression. This often requires the full attention of every crew member, leaving little time for recording fire observations. However, to improve safety and situational awareness, many of these crews post a "look-out" to make weather and fire behavior observations in their immediate and surrounding areas; these look-outs were asked to make the additional observations needed for this study.

In 2007, I sent observation packets to 15 FUMs, but few returned observations because most were assigned to tasks similar to those performed by IHCs because of the many large fires experienced that year. To ensure a more substantial return in 2008, I contacted nearly all the FUMs and IHCs nationwide. Of these, 22 FUMs and 78 IHCs agreed to make fire observations for me.

In-situ active-fire observations by wildland fire fighters

All groups that agreed to participate in my project were sent observation packets containing a Rite-in-the-Rain notebook which held the observations and directions, and a folder for storing extra forms and completed observations. Aside from the information needed to identify the observer and locate the fire (fire name, Latitude, Longitude), the crews were asked to collect the following information (a sample observation packet is included in Appendix A): *flame length*, size of flaming area or *area burning*, rate of spread (*ROS*), percent *canopy cover*, primary *fire carrier*, *fire movement* (back, flank, or head), *fire activity* (creeping, surface, torching, or crown), *other fire* activity within 1 km, and comments. Observations were recorded in units that were familiar to the fire observers in order to get the most accurate measurement. Thus *flame length* was recorded in feet and *ROS* in chains/hour (a chain is 66 feet or 20.1 m).

Of these observations, only two (*area burning* and *other fire*) were additional to the observations of fire behavior normally taken on fires. *Area burning* was meant to determine how much area on the ground was actively flaming. Because this was difficult to measure and there was a great potential for differences between observers, this and other variables were assigned to classes. I asked about the occurrence of *other fire* within 1 km to help me to determine if there may have been other energy source(s) that influence fire detection by MODIS. Observers were asked to comment on the location and activity of the *other fire* that was not directly being recorded.

Observers were encouraged to contact me with any questions they had throughout the summer. They were also encouraged to take and send me photographs of the fire behavior. I used these photographs to provide some quality control on the written observations.

Relating fire observations to MODIS fire points

Obtaining MODIS active-fire data

The MODIS data used for the comparison to active-fire observations came from the USDA Forest Service's Remote Sensing Application Center (RSAC) which receives real-time imagery from direct readout ground stations located in Salt Lake City, Utah; Madison, Wisconsin; and

Fairbanks, Alaska (Quayle 2008). Data from the NASA GSFC Rapid Response System is used to fill any gaps that may have occurred in the data collected from the ground stations to produce year-round coverage for almost all of North America. The latest fire detection algorithms (Justice *et al.*2006) are applied to the acquired imagery to produce the active-fire product available to the public on the RSAC website (http://activefiremaps.fs.fed.us/gisdata.php).

Preparing the data

Observations that were missing vital identification information (date, time, latitude, longitude) were excluded from analysis. During data entry, all measurements were converted to the same units and where *flame length* observations were written as a range, for this study I analyzed the maximum flame length observed. To represent the level of energy being emitted from the ground at that particular observation point, *flame length* and the *area burning* were multiplied together; the product is referred to as *area*FL*. Continuous variables were divided into classes based on the distribution of data (Table 2).

The time of the MODIS observation is recorded in GMT which necessitated the conversion of the observation time. This was done by determining which time zone the observation was taken in and adjusting the time accordingly. From the location of the observation points, the ecoregion class that the fire observation was take in was also determined. Observations were joined by location with the ecoregion class produced by Olson *et al.* (2001).

Classifying detection

After all columns of data were organized, the spreadsheet was saved as a text file and imported into ArcGIS 9.3. Latitude and Longitude were used as the X Y coordinates and the points were projected into the same coordinate system as the MODIS FRP points. A series of selections were performed to determine which MODIS fire points were within 500 m, 1 km, 2 km, and 3 km of each observation. These distances were chosen for several reasons. Due to the size of a MODIS pixel 500 m is the smallest unit necessary to determine if there were FRP points directly around the observations. The other distances were selected to both account for variation in distance of the observer to the observed fire, and to protect against errors in fire location recorded by the observer. A maximum of 3km is expected to account for this variability, and represents the limit to which we feel comfortable assigning an observation to a MODIS fire point. All MODIS fire points that were found within a 3 km area and within seven hours of an observation were exported.

Observations were then assigned a value of either “detect”, “no detect”, or “other better” based on several factors. In order to understand the potential that each observation had to be observed, the nearest MODIS overpass times were determined for each point by querying their individual observation locations and dates in the NASA LaRC Satellite Overpass Predictor for both the Terra and Aqua platforms. The time of overpass and sensor zenith angle was recorded for each observation. There were several groups of observations that occurred on the same day and location, but at different times. In these cases, the observation that was either closest to the time of detection, or closest to the overpass of MODIS were given the value of “detect” or “no detect”. All other observations on that day were given the value of “other better”. As an example, one observer recorded fire behavior on-the-hour from 16:00 to 23:00 GMT. Terra had an overpass time of 18:00 and Aqua has an overpass time of 21:00. There were MODIS fire points for Aqua but not for Terra; therefore the observation taken by the observer at 18:00 would be classified as “no detect”, the 21:00 observation would be a “detect”, and all others would be “other better”.

Choosing the most appropriate MODIS overpass for the observation was at times challenging. Fire behavior can change in a matter of seconds and that potential for change increases with time. In instances where an observation was in between overpasses (ex. Overpasses at 19:09 and 20:46, Observation at 19:50) the time difference between the overpass and observation were determined (-41 and 56 minutes, respectively). Fire observers are trained to take observations when fire behavior changes; therefore overpasses that occur *after* the observation are more likely to be representing the behavior noted in the observation. In the example given above, although the first overpass is closer in time, the second overpass is more likely to be representing the fire behavior at the time of the observation. With this concept of fire observer selection in mind, different time classes were created (Table 2) and assigned to each observation.

Matching fire observations to FRP

In an effort to understand the relationship between FRP and fire intensity, the “detected” observations were compared to the corresponding FRP value. This was a straight forward match for many of the fire observations since there was only one MODIS fire point near the observation in space and time. There were, however, observations that had multiple MODIS fire points around them, necessitating the development of a strategy for assigning the most likely FRP value for that observation. Of the fire points that were close in both space and time, the FRP point that was highest was chosen for comparison because I was interested in whether higher fire intensity is represented by the high FRP.

Statistics

Several statistical tests were performed using SigmaPlot 11.0 to determine the relationships between “detect” and “no detect” observations, map the probability of detection for a variety of categories in each variable, and identify the influence that certain variables have on detection. All variables were first tested for normality using the Shaparo-Wilk test. No variables were found to be normally distributed, and attempts to normalize the data using log 10, ln, exponential, reciprocal, square, center, and standardized transformations were unsuccessful. The failure to normalize the data may be due to the high proportion of all observations in the lower range of most variables. For variables with a limited number of possible responses (*canopy cover*, *fire movement*, and *fire activity*) a slight imbalance in values may have prevented the data from being normal.

Each statistical test was performed on both the entire set of observations, and on individual and selected groups of time classes. This was done to identify any difference in results for time classes, the presence of which may indicate the appropriateness of using certain time classes for analysis.

The “detect” and “no detect” observations were compared using the Mann-Whitney Rank Sum Test to identify variables were significantly ($P \leq 0.05$) different between the two groups., The percentage of “detect” and “no detect” for certain categories in each variable were then compared in order to understand the conditions for which fire detection using MODIS is most likely to detect fire. This was done by taking a variable and separating out each category then counting the number of observations for "detect" and "no detect". Chi-squared (χ^2) was calculated for each variable and when appropriate regressions were calculated using the mean value for each category.

To identify variables that most consistently and significantly ($P \leq 0.05$) influenced fire detection by MODIS, I used multiple logistic regression with both backward selection and forward selection. These variables can then be used to determine what proportion of "detect" and "no detect" they were able to predict. This will reveal if there are other variables influencing the detection of fire besides those used in the model (such as variables that were either not collected or not significant enough to be included). Many of the variables used in the models were found to be correlated with each other (e.g. *flame length*, *ROS*, and *fire activity*) so interaction terms were added where appropriate.

To calculate the correlation of FRP to other variables, I used the Spearman Rank Order Correlation. This nonparametric test allows for the comparison of data that are not normally distributed or linearly related. FRP was compared to *flame length*, *area burning*, *area*FL*, *ROS*, *fire movement*, and *fire activity* to determine the influence that each of these variables has on the value of FRP. Each of these variables was also plotted against FRP to facilitate visual comparison; perfect agreement would appear as a 1:1 line.

Case studies of fires expected to be but not detected

Several fires with on-the-ground observations of very actively burning fires viewed at low zenith angles were not detected using MODIS. Variables that may have influenced this lack of detection that were not accounted for in the active-fire observations are missing data, clouds, or smoke over the fire. I assessed the influence of these variables using data products ordered from LPDAAC using the WIST website (https://wist.echo.nasa.gov/api/). The land surface temperature daily LB Global 1 km V005 (MOD11A1, MYD11A1) was used to observe missing data over the fire area, and the surface reflectance daily L2G Global 1 km sin grid V005 (MOD09GA, MYD09GA) was used to determine the presence of cloud or smoke over the fire. After the images were ordered for the date and geographic location of on-the-ground observations, the MODIS reprojection tool was used to select the desired bands in each image (Emis 31 and Bands 1 to 4), convert each image into a GEOtiff, select out the fire area, and reproject it into a common projection. Using the four bands retrieved from the surface reflectance images, a true (Bands 1, 4, and 3) and false (2, 1, and 4) color composite were generated in ArcGIS 9.3 for visual assessment of both cloud and smoke. The location of the observations was then overlain on these images to determine if missing data, cloud, or smoke may have caused the observation to not be detected.

RESULTS

Fire observations

Of the 100 groups of wildland firefighters that were asked to participate, 32 groups (32%) returned observations. In total, 405 observations were recorded with 265 remaining after the removal of invalid entries and those observations classed as “other better”. Fire observations were taken in 13 states: Arizona, California, Colorado, Florida, Idaho, Montana, Nevada, New Mexico, Oregon, Texas, Utah, Washington, and Wyoming (Figure 2), with 23 different ecoregions represented. Of all observations, 32 (12%) occurred in grasslands, 39 (15%) in shrublands, and 194 (73%) in forests.

Variables that are significantly different between “detect” and “no detect”

Of 265 observations, 91 (34%) were classified as “detect” and 174 (66%) were classified as “no detect”. In order to understand of the effects of different variables on the detection of fire by MODIS, I looked at the relationship between variables for “detect” and “no detect” observations using the Mann-Whitney Rank Sum Test. Observations were compared using selected groups of time classes as there were too few observations in individual time classes for individual analyses. (Table 3). None of the variables differed significantly for fire behavior observations taken after the nearest MODIS overpass (≥-1:30 to -0:01). For all other groups of time classes, *sensor zenith angle* differed significantly between “detect” and “no detect”, with *flame length*, *ROS*, and *fire activity* as significant in most groups, and *area*FL* and *area burning* as significant in some cases. Although the time classes 1 and 2 (≥-1:30 to -0:01) did not produce significant differences when tested separately, they do appear to hinder and in some cases contribute when they are assessed with the addition of other time classes (Table 3).

Proportion of detection for different categories in each variable

The variables found to be significant in the above analyses also exhibited predicted trends as the values of the variables changed (Figure 1). Variables that had the most significant change in detection as the values changed were *fire activity* (χ^2 test, $p = 0.012$), *sensor zenith angle* (χ^2 test, $p = 0.002$), *ROS* (χ^2 test, $p = 0.12$), and *flame length* (χ^2 test, $p = 0.12$). For *fire activity,* detection ranged from 5% for creeping fires to 56% for torching fires. Detection with the variable *sensor zenith angle* ranged from 12% for 60 to 70^o from nadir to 56% for 0 to 10^o from nadir.

To assess the proportion of fires detected under ideal observation conditions, *sensor zenith angle* and *fire activity* (the most reliable variables) were used to organize the data. Observations that had the lowest *sensor zenith angle* and the highest *fire activity* were assessed to see at what values MODIS has the highest proportion of detection. At a *sensor zenith angle* of 0 to 20˚ and *fire activity* of torching and greater, MODIS was able to detect 66% of the observed fires (Figure 3). Other combinations with a *sensor zenith angle* from 0-10˚ and 0-20˚, and *fire activity* of surface or greater, were detected an average of 55% of the time.

Variables that explain "detect" or "no detect"

Each of the *time class* groups were tested using multiple logistic regression to assess the changes in significant variables and overall model performance (Table 3). For each group, several models were developed that had significant variables, and one model for each group was chosen based on the ability of the variables to predict detection or no detection and the number of variables used in the model. The better the model is at predicting "detect" and "no detect", the more influential the variables used in the model are in detection by MODIS. Each model provided the Actual "detect" and "no detect" and the Predicted "detect" and "no detect". In a model where the variables explain all detection and no detection, the Predicted would equal Actual (Table 4), but since all models had at least some other variables influencing detection, the models with the highest proportion Predicted were favored. The percentages shown here (Table 5) should not be confused with the likelihood that MODIS will detect a fire; they are simply used to determine which variables are most influential in the detection of fire by MODIS. Using time classes three through five (0:00 to ≥+1:30) produced the best combination of predicted "detect" and predicted "no detect" (Table 5).

Sensor zenith angle and *fire activity* were the most influential variables in fire detection by MODIS (Table 5). Other variables that were found to be significant in some models but may not have produced the best model for a group of time classes are *area burning*, *area*FL, ROS,* and *flame length.*

The relationship of FRP to active-fire observations

Using Spearman's Rank Order, six fire behavior variables were assessed for a relationship to FRP (*flame length*, *area burning*, *area*FL*, *ROS*, *fire movement*, and *fire activity*). Although *flame length* was significantly correlated with the value of FRP (P = 0.031), the R^2 was 0.14. None of the variables were close to a 1:1 relationship, and all of the R^2 values were less than 0.14.

Case studies of fires expected to be but not detected

I examined all of the actively burning fires with on-the-ground observations that were not detected by MODIS under ideal *sensor zenith angle* (0 to 10˚) and *fire activity* (surface and greater) to determine the influence of missing data, cloud, and smoke on fire detection. Of the 12 fires I examined, five observations were directly obscured by cloud with the possible contribution of smoke (one of these also had missing data) (Figure 5). Three had clouds near the observation that may have impeded detection, and four (one third of those I examined) had no missing data and no visible obstructions. Of the four that were not obstructed, two had no difference in time between observation and overpass and two had observations that occurred after the nearest overpass. The recorded notes for one of the observations indicates that it was taken on a portion of a wildfire that was intentionally ignited as part of the suppression strategy; this ignition took place after the MODIS overpass suggesting that there was not similar fire activity at that location before the time of observation. The presence of a time difference does not in itself explain the detection of fires since there are many instances where fire behavior remains similar over time. It is possible, however, to see a shift in fire behavior with any difference in time.

DISCUSSION

Fire observations

Overall, I was pleased with the rate of return and the quality of observations produced by fire fighters. Many fire fighters expressed appreciation for being included in the study and all were interested in the results produced. Although this is a means of data collection that should be used sparingly so as not to interfere with the primary duties of the fire fighters, we found them to be enthusiastic and interested in the scientific process and willing to do similar observations in the future. It is very important that the research be coordinated with fire personnel well in advance and with the help of a liaison very knowledgeable of fire fighting and fire management (Lentile *et al.* 2007). Because I am a fire fighter with 7 years of experience, I may have been more successful in getting fire fighters to take observations.

Although the 20% expected and the 32% of actual return may appear relatively low, there are several reasons that we anticipated and planned for these numbers, and some possible options for increasing the rate of return in future studies. One of the main advantages of using fire fighters to take observations (namely their location on wildland fires) can also become a disadvantage because observations are secondary to their primary assignments on the fires. Assignments on fires vary in their difficulty and need for the devotion of all resources. Many crews found themselves too consumed with their primary duties to take observations. Sometimes, the crews were not in the locations to take active-fire observations (for example if they were preparing areas in advance of the fire or working in areas where the fire had already burned). Regardless of the assignment that a crew is on, the logistics of running an effective team of fire fighters can be very demanding and may have caused some groups to set the observations aside. Although these factors are hard to avoid, the rate of return on the observations may have been improved if crews were reminded directly before the start of the season and mid-season. This would not remove the extraneous circumstances of their assignments on fires, but it would reduce the loss from simply leaving the observation booklet behind.

Variables influencing fire detection using MODIS

As expected, MODIS overpasses that occur at the same time or after an observation are more likely to pick up the observed fire behavior. This was supported by the results from the Mann-Whitney Rank Sum test (Table 3) as well as the multiple logistic regression (Table 4). Overall, *sensor zenith angle* and *fire activity* were the most reliable variables, with *area burning*, *flame length*, and *ROS* also important in determining whether or not a fire was detected by MODIS. Some of the variables used in this analysis performed as expected, while others did not.

Sensor zenith angle
As *sensor zenith angle* increased, the detection rate decreases from 56% at 0 to 10 ^{o}, to 12% at 60 to 70 ^{o} (χ^2 test, p=0.002). This is consistent with the findings by Kaufman *et al.* (1998), Giglio *et al.*(1999), Morisette *et al.*(2005*b*) and Schroder *et al.*(2005). This decrease in detection is related to the increased pixel size at larger scan angles which reduces the fire size relative to the pixel size (Giglio *et al.*1999). This variable was found to be statistically different between "detect" and "no detect" for almost all groups of time classes, and was always a significant variable in the best model for predicting detection

Fire activity
As fire activity increased from creeping to crowning, the probability of detection increased as I expected. The detection rate for a creeping fire was 5% increasing to 56% for torching (χ^2 test, p = 0.012). The percentage of detection leveled off after torching indicating that there is a less noticeable difference in fire detection between torching and crowning. The performance of this variable may be attributed to the ease with which fire observers are able to classify it since it is a common measure of fire behavior. This variable is well suited to observe general fire behavior as opposed to the spikes in fire activity that are observed by *flame length* which essentially is a finer resolution, continuous measure of the fire activity. This becomes very important when the timing of the MODIS over-pass is not coincident with the fire behavior observation on-the-ground, where although a fire had occasional bursts of high intensity, the general fire behavior was better described as a "surface" fire rather than a "torching" fire. *Fire activity* was also consistently different between "detect" and "no detect" and contributed to most of the best models for predicting detection.

Area burning
I expected high variability in this variable between observations because of the difficulty in ocularly estimating area. My hope was to capture the relative area on the ground which I believe was accomplished by placing the data collected into broad classes. Observations with 0.1 to 5 m^2 of active flaming were detected 25% of the time, compared to observations with 100000+ m^2 which had a 48% detection rate (χ^2 test, p = 0.37). These results are consistent with previous studies which indicate that larger fires (as represented by the number of fire pixels in the reference image) have a much higher detection rate (Morisette *et al.* 2005a, b, Csiszar *et al.* 2006, Hawbaker *et al.* 2008, Schroeder *et al.* 2008). *Area burning* for "detect" and "no detect" was only found to be statistically significant for time classes three through five (0:00 to ≥+1:30) and did not contribute to any of the best models, although it was a significant variable in many models that were not selected as the best predictors of fire detection.

Flame length
As expected, fires were more likely to be detected at high flame lengths. The detection rate for fires with flame lengths of 0 to 5 m was 25%, it was as high as 77% for 20.1 to 30 m flame lengths, but was 42% for flame lengths of 30.1+ m (χ^2 test, p = 0.12). The reduced performance of this variable compared to others may have been caused by differences between observers, but it is more likely due to the rapidly changing nature of fire which provided for a shift in flame length between the time the fire was observed and the time of MODIS overpass. *Flame length* contributed to several models and was statistically different between "detect" and "no detect" for most groups of time classes.

Rate of spread

Although it cannot be detected with one observation at a single point in time, a higher ROS is typically associated with higher fire intensity. This variable may have been challenging to measure by the fire observers depending on the distance from the fire, vegetation the fire is burning in, and the observer experience. A ROS of 0.1 to 1 ch/hr was detected 29% of the time, while fires with ROS of >40ch/hr were detected up to 63% (χ^2 test, p = 0.12). This variable was found to be significantly different for "detect" and "no detect" for most of the time class groups, but as with *area burning* was only significant in models that were not selected as the best predictors of fire detection.

*Area*flame length*

This variable was created to represent the energy that is being released from fire by multiplying *area burning* by *flame length*. It was significantly different for several time class groups, and was also a significant variable in several of the best models. There was a large amount of variability in proportion of "detect" and "no detect" between classes which produced an insignificant χ^2 with p = 0.34.

Other variables

There were several variables that did not perform as well as initially expected. Smith *et al.* (2005) were able to distinguish between head fires and back fires using FRP in African grasslands. We failed to do so, perhaps because of the diversity of vegetation types and variation in intensity for head fires in the grasslands, shrublands, and forests sampled in this study. *Canopy Cover* did not affect detection of fires as expected, but the observations may not have fully represented the many combinations of canopy cover and fire behavior possible. Schroeder *et al.* (2008) suggested that detecting understory fires may be more difficult with a mid-near infrared detection algorithm. In open stands, however, fires tend to burn in a long straight line with limited flaming front depth, generating less contrast to surrounding pixels making detection more difficult. Detection did not vary with *ecoregion class* which may also be attributed to the characteristics of the fires that burns in grasslands and shrublands (i.e. burning in a long straight line). Again, additional observations looking specifically at the cover type would be needed to draw any definite conclusions. The presence of *other fire* was also not found to significantly contribute to detection by MODIS.

The relationship of FRP to active-fire observations

By using the middle infrared region of the electromagnetic spectrum, FRP has been used successfully to gather information on the combustion process (Lentile *et al.*2006). Wooster and Zhang (2004) found that the fires in Russia emitted considerably less energy than those in North America; Smith and Wooster (2005) observed an order of magnitude difference between the FRP of heading fires versus backing fires in African savannas. FRP has also been found to be related to the total amount of fuel combusted (Kaufman *et al.*1998; Wooster *et al.*2003; Roberts *et al.* 2005; Wooster *et al.* 2005). Despite these findings, this study was not able to demonstrate a relationship between any of the *in-situ* fire behavior observations and FRP. The variety of vegetation types sampled may have contributed to the lack of relationship since there may be differences in the energy released between vegetations types with similar fire behavior characteristics. More analysis specifically evaluating the performance of FRP should be conducted to better understand its relationship to different fire intensity levels in different vegetation types.

Case studies of fires expected to be but not detected

Of the 12 fires assessed for missing data, cloud, and smoke, eight (66%) were likely obscured by cloud or smoke. The influence of these two variables on the detection of fire by MODIS has been previously observed (Kaufman *et al.* 1998, Hawbaker *et al.* 2008, Schroeder *et al.* 2008, Csiszar *et al.* 2006). Missing data can also impede detection (Schroeder *et al.* 2008) but was only present over one of the 12 observations (an observation that was also obscured by smoke). Of the four non-obstructed observations, a change in fire behavior between the time of observation and the time of overpass may have accounted for the lack of detection. Sunglint may also have been a contributing factor (Kaufman *et al.* 1998, Schroeder *et al.* 2008)

Although this is only a small subset of the fire observations that were not detected, this analysis helps characterize additional variables that influence fire detection. The spatial and temporal variability of the fire observations would make analysis of every point logistically difficult, but would be a useful step to fully understanding the influence of missing data, cloud, and smoke over all observations. Future work will look specifically at the influence of these variables on detection.

Limitations

The information presented here is useful for better understanding the variables that influence fire detection with MODIS imagery and to get an idea of the likelihood of detection under certain conditions. Although the percent of “no detect” I observed will likely vary with geographic location or additional active fire observations, I feel confident that the variables presented here have a large influence on the active fire detection of MODIS.

Using data from multiple observers with varying experience levels is one limitation to this method of data collection. Further, the time between observation and MODIS overpass may be considered a limitation to this study. Because fire behavior can change from minute to minute and hour to hour, lack of detection could result from even minor differences in time of observation and image acquisition. Although we could have predetermined the exact overpass time for different locations across the country it was not possible to dictate when observations would be taken. We also felt that by limiting the observations times, we might discourage the collection of some observations, and possibly limit the ability of these data to be used in other forms of analysis.

There may be some instances where the fire observations were mis-classified into “detect” or “no detect”. Mis-classifying into “detect” may have occurred if there was other significant activity within 3 km that was the actual contributor to MODIS detection. In general, however, fire fighting forces are placed where fires are actively burning, and if other activity is taking place nearby, it is likely experiencing similar fire conditions. Mis-classifying "no-detect" may occur more commonly, and can be caused by location accuracy of Global Positioning System units and MODIS, especially at larger view angles (Wolfe *et al.* 2002).

If fire is detected, there may be more fire contributing to that detection than is noted in the observation, which may lead to detection of apparently lower intensity fires. Observers were asked to make note of other fire activity that might be occurring within 1 km of the observation, and although this variable was not found to be related to detection, there may be instances where it was a contributor.

Observations were primarily taken in the western US during summer. I was not able to draw solid conclusions about the performance of the MODIS active fire product between the West, Great Plains, and the East as done by Hawbaker *et al.* (2008). A comparison between observations taken in different ecoregions may be possible with this approach to data collection, but more observations would need to be gathered to fully represent selected ecoregions.

Implications

Using fire fighters to make fire behavior observations on actively burning wildfires has given us data that is not easily obtained otherwise. Fire behavior and effects data from actively burning fires has been collected on prescribed fires and by research scientists on actively burning wildfires (Lentile *et al.* 2007). The former are valuable but limited to a few fires, and the latter are limited to locations and conditions where prescribed fires occur. Here, fire behavior observations were obtained from a wide variety of burning conditions on actively burning wildfires.
Fire managers that choose to use MODIS as an active fire observation tool will now have a better understanding of its strengths and limitations. Although they may not be able to pin-point the level of fire activity, the presence of an active fire pixel (or pixels) may indicate a certain level of fire activity since detections rates increase proportionally with this variable (torching fires detected 56% of the time). MODIS will be less useful for detecting actively burning fires when the overpass is predicted to have a high sensor zenith angle (http://www-air.larc.nasa.gov/tools/predict.htm) or the fire area is covered by clouds.

Even under the best conditions, 34% of all fires may not be detected using MODIS. Although the observed fires may account for the majority of biomass burning (Kaufman *et al.* 1998*b*) adjustments may still need to be made to the global active fire estimates, so they are more representative of actual fire occurrence.

REFERENCES

Anonymous (2009) Quadrennial Fire Review. Available at http://www.nifc.gov/QFR/QFR2009Final.pdf [Verified April 2009]

Butler BW, Cohen J, Latham DJ, Schuette RD, Sopke P, Shannon KS, Jimenez D, Bradshaw LS (2004). Measurements of radiant emissive power and temperatures in crown fires. *Canadian Journal of Forest Research* **34**,1577-1587.

Crutzen PJ, Heidt LE, Krasnec JP, Pollock WH, Seiler W (1979) Biomass burning as a source of atmospheric gases: CO, H2, N2O, NO, CH3Cl, and COS. *Nature* **282,** 253-256.

Crutzen PJ and Andreae MO (1990) Biomass burning in the tropics: impact on atmospheric chemistry and biogeochemical cycles. *Science* **250,** 1669-1678.

Csiszar IA, Morisette JT, Giglio L (2006) Validation of active fire detection from moderate-resolution satellite sensors: the MODIS example in northern Eurasia. IEEE *Transactions on Geoscience and Remote Sensing* **44**, 1757-1764.

Dozier J (1981) A method for satellite identification of surface temperature fields of subpixel resolution. *Remote Sensing of Environment* **11**, 221-229.

Eva H, Lambin EF (1998) Burnt area mapping in detection of Central Africa using ATSR data. *International Journal of Remote Sensing* **19,** 3473–3497.

Flannigan MD and Vonder Haar TH (1986) Forest fire monitoring using NOAA satellite AVHRR. *Canadian Journal of Forest Research* **16**, 975–982.

Fraser RH, Li Z, Cihlar J (2000) Hot spot and NDVI differencing synergy (HANDS): A new technique for burned area mapping over boreal forest. *Remote Sensing of Environment* **74**, 362-376.

Giglio, L, Kendall JD, and Justice CO (1999) Evaluation of global fire detection algorithms using simulated AVHRR infrared data. *International Journal of Remote Sensing,* **20,**1947–1985.

Giglio L, Descloitres J, Justice CO, Kaufman YJ (2003) An enhanced Contextual Fire Detection Algorithm for MODIS. *Remote Sensing of Environment* **87,** 273-282.

Hawbaker TJ, Radeloff VC, Syphard AD, Zhiliang Z, Stewart SI (2008) Detection rates of the MODIS active fire product in the United States. *Remote Sensing of Environment* **112,** 2656-2664.

Holden ZA, Smith AMS, Morgan P, Rollins MG, Gessler PE (2005) Evaluation of novel thermally enhanced spectral indices for mapping fire perimeters and comparisons with fire atlas. *International Journal of Remote Sensing* **26**, 4801–4808.

IPCC (2007) Intergovernmental panel on climate change fourth assessment report. Available at http://www.ipcc.ch/ipccreports/ar4-wg1.htm [Verified April 2009]

Justice C, Giglio L, Boschetti L, Roy D, Csiszar I, Morisette J, Kaufman Y (2006) MODIS fire products. *Algorithm Technical Background Document*. Ver. 2.3, EOS ID#2741. Available at http://modis.gsfc.nasa.gov/data/atbd/atbd_mod14.pdf [Verified April 2009]

Justice CO, Giglio L, Korontzi S, Owens J, Morisette JT, Roy D, Descloitres J, Alleaume S, Petitcolin F, Kaufman Y (2002) The MODIS fire products. *Remote Sensing of Environment* **83**, 245–263.

Kaufman YJ, Justice CO, Flynn LP, Kendall JD, Prins EM, Giglio L, Ward DE, Menzel WP, Setzer AW (1998a) Potential global fire monitoring from EOS-MODIS. *Journal of Geophysical Research* **103**, 32215-32238.

Kaufman YL, Kleidman RG, King MD, (1998b) SCAR-B fires in the tropics: properties and remote sensing from EOS-MODIS. *Journal of Geophysical Research* **103**, 31 955-31 968.

Kaufman YJ, Setzer A, Ward D, Tanre D, Holben BN, Menzel P, Pereira MC, Rasmussen R (1992) Biomass burning airborne and spaceborne experiment in the Amazonas (BASE-A). *Journal of Geophysical Research* **97**, 14581-14599.

Kaufman YJ, Tucker CJ, Fung I (1990) Remote sensing of biomass burning in the tropics. *Journal of Geophysical Research* **95**, 9927–9939.

Kennedy PJ, Belward A S, Gregoire JM (1994) An improved approach to fire monitoring in West Africa using AVHRR data. *International Journal of Remote Sensing* **15** 2235–2255.

Key, C.H. (2005) Remote sensing sensitivity to fire severity and fire recovery. In 'Proceedings of the 5th International Workshop on Remote Sensing and GIS Applications to Forest Fire Management: Fire Effects Assessment'. (Eds J De la Riva, F Perez-Cabello, E Chuvieco) pp. 29-39. (Universidad de Zaragoza: Spain)

Lentile LB, Holden Z, Smith AMS, Falkowski MJ, Hudak AT, Lewis SA, Morgan P, Gessler PE, Benson NC (2006) Remote sensing techniques to assess active fire and post-fire effects. *International Journal of Wildland Fire* **15**, 319-345

Lentile LB, Morgan P, Hardy C, Hudak A, Means R, Ottmar R, Robichaud P, Sutherland E, Szymoniak J, Way F, Fites-Kaufman J, Lewis S, Mathews E, Shovic H, Ryan K. (2007) Value and Challenges of Conducting Rapid Response Research on Wildland Fires. USDA Forest Service General Technical Report. GTR 193. Fort Collins, CO, 16 p.

Matson M, and Dozier J (1981) Identification of subresolution high temperature sources using a thermal IR sensor. *Photogrammetric Engineering and Remote Sensing* **47**, 1311-1318.

Morisette JT, Giglio L, Csiszar I, Justice CO (2005*a*) Validation of the MODIS active fire product over Southern Africa with ASTER data. *International Journal of Remotes Sensing* **26,** 4239-4264.

Morisette JT, Giglio L, Csiszar I, Setzer A, Schroeder W, Morton D, Justice CO (2005*b*) Validation of MODIS active fire detection products derived from two algorithms. *Earth Interactions* **9**(9), 1-25.

Mottram GN, Wooster MJ, Balster H, George C, Gerrard F,Beisley J (2005) The use of MODIS-derived fire radiative power to characterise Siberian boreal forest fires. In 'Proceedings of the 31st international symposium on remote sensing of environment, 20–24 June 2005. (Saint Petersburg: Russian Federation). Available at http://www.isprs.org/publications/related/ISRSE/html/papers/681.pdf [Verified April 2009]

NWCG (2004) Fireline Handbook: Appendix A. pp. A 58. PMS 410-1, NFES 0065. National Wildfire Coordinating Group, Washington, D.C.

NWCG (2006) Incident Response Pocket Guide: Fire Size Class. pp.96. PMS 461, NFES 1077. National Wildfire Coordinating Group, Washington, D.C.

Olson D, Dinerstein ME, Wikramanayake ED,. Burgess ND, Powell GVN, Underwood EC, D'amico JA, Itoua I, Strand HE, Morrison JC, Loucks CJ, Allnutt TF, RickettsTH, Kura Y, Lamoreux JF, Wettengel WW, Hedao P, Kassem KR (2001) Terrestrial Ecoregions of the World: A New Map of Life on Earth. BioScience **51**, 933-938

Penner, JE, Dickenson RE, O'Neill CA (1992) Effects of aerosol from biomass burning on the global radiation budget. *Science* **256,** 1432-1434.

Riggan PJ, Tissell RG, Lockwood RN, Brass JA, Pereira JAR, Miranda HS, Miranda AC, Campos T, Higgins R (2004) Remote measurement of energy and carbon flux from wildfires in Brazil. *Ecological Applications* **14**, 855–872.

Roberts G, Wooster MJ, Perry GLW, Drake N, Rebelo L-M, Dipotso F (2005) Retrieval of biomass combustion rates and totals from fire radiative power observations: Part 2 – applications to southern Africa using geostationary SEVIRI imagery. *Journal of Geophysical Research* **110**, D24311.

Rouse JW, Haas RH, Schell JA, Deering DW, Harlan JC (1974) Monitoring the vernal advancement of retrogradation of natural vegetation. NASA/GSFC, Type III, Final Report, Greenbelt, MD, USA, pp. 1 ± 371.

Schroeder W, Morisette JT, Csiszar I, Giglio L,Morton D,Justice CO (2005) Characterizing vegetation fire dynamics in Brazil through multisatellite data: Common trends and practical issues. *Earth Interactions* **9**, 1−26.

Schroeder W, Prins E, Giglio L, Csiszar I, Schmidt C, Morisette JT, Morton D (2008) Validation of GOES and MODIS active fire detection products using ASTER and ETM+ data. *Remote Sensing of Environment* **112,** 2711-2726

Smith AMS, Wooster MJ (2005) Remote classification of head and backfire types from MODIS fire radiative power observations. *International Journal of Wildland Fire* **14**, 249-254.

Stroppiana D, Pinnock S, Pereira JMC, Grégoire J-M (2002) Radiometric analysis of SPOT-VEGETATION images for burnt area detection in Northern Australia. *Remote Sensing of Environment* **82**, 21–37. doi:10.1016/S0034-4257(02)00021-4

Silva JMN, Pereira JMC, Cabral AI, Sa ACL, Vasconcelos MJP, Mota B, Grégoire J-M (2003) An estimate of the area burned in southern Africa during the 2000 dry season using SPOT-VEGETATION satellite data. *Journal of Geophysical Research* **108**, 8498.

Salvador R, Valeriano J, Pons X, Díaz-Delgado R (2000) A semi-automatic methodology to detect fire scars in shrubs and evergreen forests with Landsat MSS time series. *International Journal of Remote Sensing* **21,** 655–671.

Theobald and Romme (2007). Expansion of the US wildland-urban interface. *Landscape and Urban Planning* **83,** 340-354.

Trollope WSW, Trollope LA, Potgieter ALF, Zambatis N (1996) SAFARI-92 characterization of biomass and fire behavior in the small experimental burns in Kruger National Park. *Journal of Geophysical Research* **101**, 23 531-23 540.

Wilson EH, Sander SA (2002) Detection of forest harvest type using multiple dates of Landsat TM imagery. *Remote Sensing of Environment* **80**, 385-396.

Wolfe RE, Nishihama M, Fleig AJ, Kuyper JA, Roy DP, Storey JC, Patt FS (2002) Achieving sub-pixel geolocation accuracy, in support of MODIS land science. *Remote Sensing of Environment* **83**, 31-49.

Wooster MJ (2002) Small-scale experimental testing of fire radiative energy for quantifying mass combusted in natural vegetation fires. *Geophysical Research Letters* **29**, 2027.

Wooster MJ, Roberts G, Perry GLW, Kaufman YJ (2005) Retrieval of biomass combustion rates and totals from fire radiative power observations: Part 1 - Calibration relationships between biomass consumption and fire radiative energy release. *Journal of Geophysical Research* **110**.

Wooster MJ, Zhukov B, Oertel D (2003) Fire radiative energy for quantitative study of biomass burning: derivation from the BIRD experimental satellite and comparison to MODIS fire products. *Remote Sensing of Environment* **86,** 83-107.

Wooster MJ, Zhang YH (2004) Boreal forest fires burn less intensely in Russia that in North America. *Geophysical Research Letters* **31**,L20505.

Table 1. Validation results for the MODIS active fire product

Author/Date	Description	Finding
Giglio et al. (2003)	- Simulated fire scenes - 10 different biomes - Various fire sizes	- Across all biomes, identified the smallest fire size to be detected 50% of the time: for flaming fire ~100m^2 for smoldering fire 10 to 20 times larger
Cardosa et al. (2005)	- Study area: Brazilian Amazon - Compared visual ground observation of fire and no-fire to AVHRR and MODIS	- Omission errors higher than commission errors - Fire products are limited in their ability to represent fire activity - Interpretation of these products can be improved with ground-based analysis
Morisette et al. (2005a)	- Study area: Southern Africa - Validation of MODIS with ASTER	- A cluster of 25 to 34 ASTER fire pixels needed for 50% probability of MODIS detection
Morisette et al. (2005b)	- Study area: Brazilian Amazon - Validation of two detection algorithms of MODIS with ASTER	- 0.01% commission - 47+ ASTER pixels
Csiszar et al. (2006)	- Study area: Northern Eurasia - Validation of MODIS with ASTER	- 0.002% commission - ~60 ASTER pixels
Hawbaker et al. (2008)	- Study area: United States - MODIS fire detections compared to reference fires ≥ 18 ha - Fire size, confidence of MODIS, cloud over, and region were looked at as possible reasons for detection or no detection	- 82% of the reference fires were detected - More cloud over fires that were not detected - Fire detection increased with fire size - Better detection rates in the western US
Schroeder et al. (2008)	- Study area: Brazilian Amazon - Validation of MODIS and GEOS with primarily ASTER and Landsat ETM+ - Identify options for reducing commission errors of MODIS and GEOS	- 75% of fires samples omitted by the instantaneous product - 35% commission errors over areas of active deforestation

Table 2: Variables and classes used for analysis. *Area burning* refers to the area on the ground that contains flame. *Time difference* refers to the time between a MODIS overpass and an active fire observations (“+” means the observation was taken before the overpass, “-” means the overpass occurred before the observation). *ROS* (rate of spread) is how fast the fire is moving at a given time. *Flame length* is measured from the base of the flame to the tip. *Area* burning is the amount of area on the ground that is actively flaming. *Area * FL (flame length)* is a metric designed to represent a relieve activity level using a combination of *area burning* and *flame length*. *Fire activity* classes are broad groups used to define the behavior of the fire. *Fire movement* classes are used to define the way the fire is spreading.

Time class		ROS		Flame Length		Area burning		Area*FL		Fire Activity		Fire Movement	
Hrs:Min		*Chains/hr*		*Meters*		*Meters^2*		*Meters^3*		Creeping (Cr)	1	Back	1
≥-1:30	1	0.1 to 1	1	0.01 to 0.5	1	0.1 to 5	1	25	1	Cr/S	2	Back/Flank	2
-0:01 to -1:29	2	1.1 to 2	2	0.51 to 1	2	5.1 to 15	2	100	2	Surface (S)	3	Flank	3
0:00	3	2.1 to 5	3	1.1 to 2	3	15.1 to 50	3	350	3	S/T	4	B/F/H	4
0:01 to 1:29	4	5.1 to 10	4	2.1 to 4	4	50.1 to 300	4	800	4	Torching (T)	5	Flank/Head	5
≥1:30	5	10.1 to 20	5	4.1 to 10	5	300.1 - 4000	5	1500	5	T/C	6	Head	6
		20.1 to 40	6	10.1 to 20	6	4001 to 1000	6	4000	6	Crowning (C)	7		
		40.1 +	7	20.1 to 30	7	1001 to 40000	7	9000	7				
				30.1+	8	40001 to 100000	8	14000	8				
						100001 +	9	30000	9				
								42000	10				
								130000	11				
								450000 +	12				

Table 3: Explanatory power of variables based upon Mann-Whitney Rank Sum test. Shaded p-values are <0.05. Significance here indicates a difference between "detect" and "no detect" observations. Observations in all time classes were compared, as well as different combinations of time classes to determine the appropriateness of using all time classes in analysis.

	Sensor Zenith Angle	Flame Length	Area Burning	Area*FL	ROS	Canopy	Fire Movement	Fire Activity	Other Fire	Ecosystem Class
≥-1:30 to -0:01	0.081	0.118	0.789	0.957	0.41	0.391	0.897	0.249	0.359	0.074
≥-1:30 to 0:00	0.007	0.116	0.149	0.065	0.073	0.746	0.642	0.081	0.854	0.994
≥-1:30 to +1:29	<0.001	0.012	0.156	0.048	0.017	0.3	0.299	0.002	0.539	0.351
-1:29 to +1:29	<0.001	0.018	0.162	0.058	0.04	0.19	0.493	0.006	0.849	0.364
-1:29 to ≥+1:30	<0.001	0.002	0.1	0.013	0.007	0.212	0.33	0.002	0.584	0.546
0:00 to ≥+1:30	0.001	0.002	0.047	0.006	0.003	0.358	0.118	<0.001	0.637	0.668
0:01 to ≥+1:30	0.002	0.005	0.348	0.087	0.015	0.272	0.249	0.001	0.781	0.505
All	<0.001	0.002	0.105	0.012	0.003	0.313	0.245	<0.001	0.924	0.626

Table 4: This is the model chosen for time classes 3-5 (0:00 to ≥+1:30). If the variables in the model were perfect predictors of the detection of MODIS, the two highlighted boxes would equal the total Actual "detect" and "no detect". The variables in the model with the highest proportion in the highlighted boxes were considered good predictors of detection by MODIS.

	Predicted "no detect"	Predicted "detect"	Totals
Actual "no detect"	117	16	133
Actual "detect"	28	26	54
Totals	145	42	187

Table 5: Each group of time classes was analyzed to identify the variables that most influenced the detection of fire by MODIS. For each group of time class, the best model was selected based on the ability of the variables to predict detection. Time classes 3-5 (0:00 to ≥+1:30) had the highest predicted "detect" and "no detect". The percentage that the model was not able to predict indicates that other variables not accounted for in the model were influencing detection, these variables may be those that were either not found to be significant enough to be included, or variables that were not collected in this study.

	Ability of variables to predict detection		**P value of variables in the model**			
Time Class	% Predicted from Actual "detect"	% Predicted from Actual "no detect"	Sensor Zenith Angle	Fire Activity	Area*FL	Flame Length
≥-1:30 to -0:01		No model with significant variables				
≥-1:30 to 0:00	68.8	43.1	0.007			
≥-1:30 to +1:29	57.5	76.9	<0.001	<0.001	0.007	
-1:29 to +1:29	47.6	78	<0.001	0.01		
-1:29 to ≥+1:30	52.6	77.7	<0.001	0.002	0.006	
0:00 to ≥+1:30	48.1	88	<0.001	0.01	0.001	
0:01 to ≥+1:30	55	80.3	0.02	0.008		0.019
All	55.7	75.3	<0.001	<0.001	0.002	

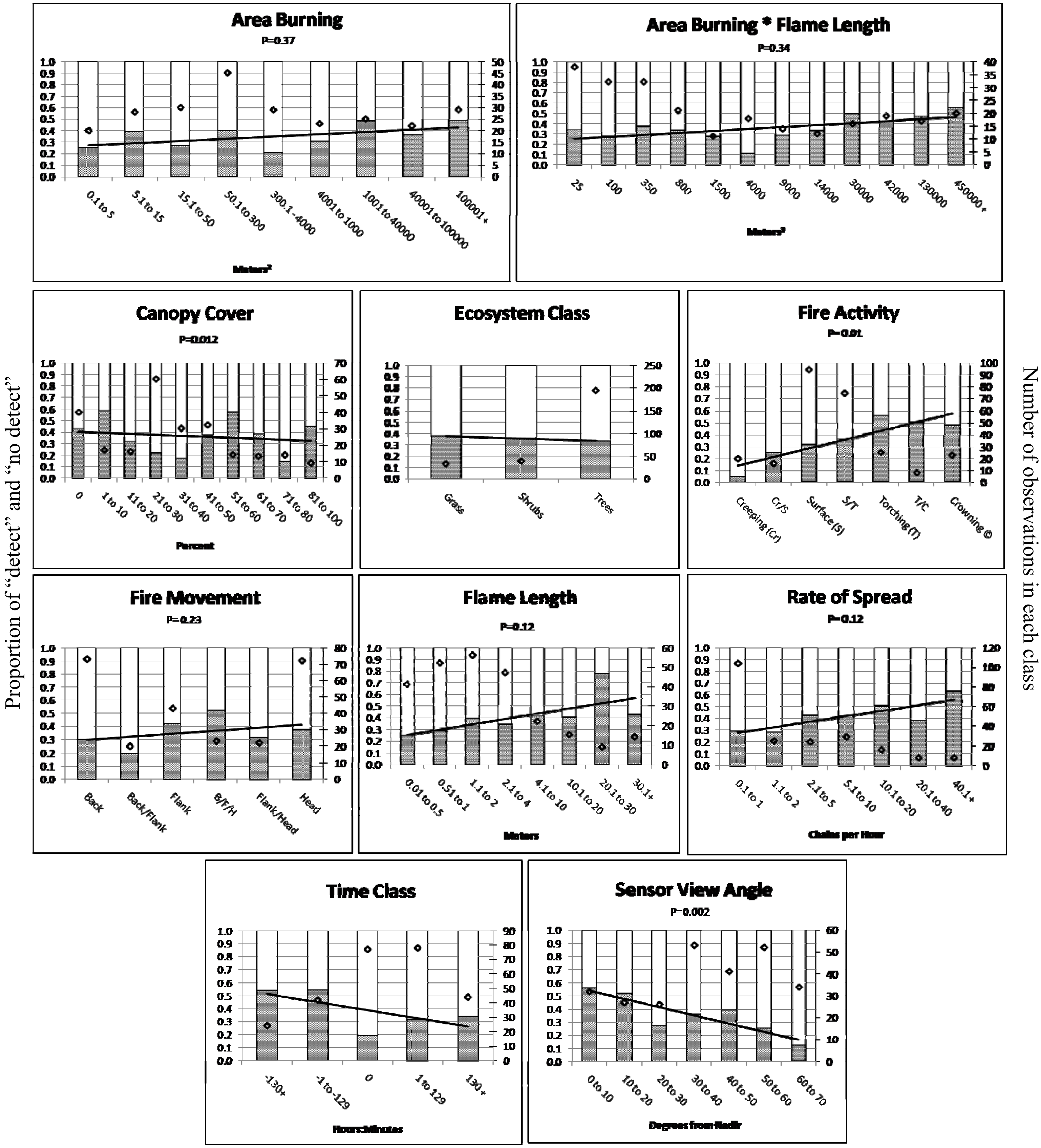


Figure 1: The proportion of fire observations that were detected (grey) and not detected (white) using MODIS, relative to characteristics observed on the ground. The P values displayed are for Chi-squared (χ^2) tests. The line displays the trend of the data, and the points represent the number of observations in each category.

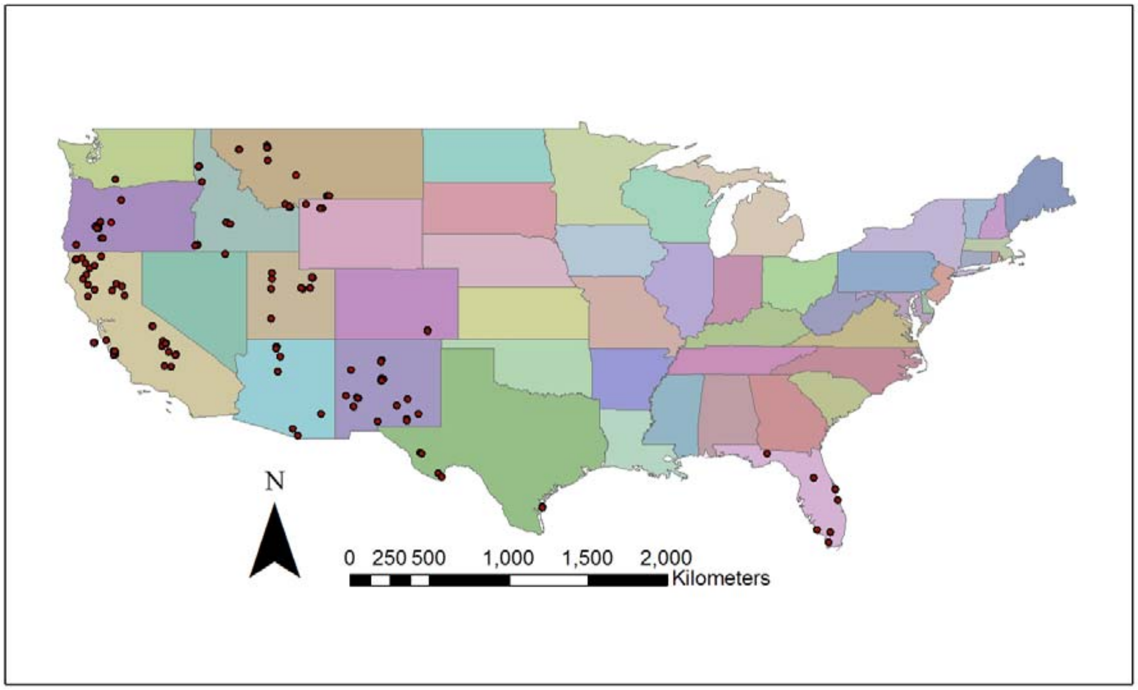


Figure 2: Points represent the locations of the active fire observations taken by fire fighters.

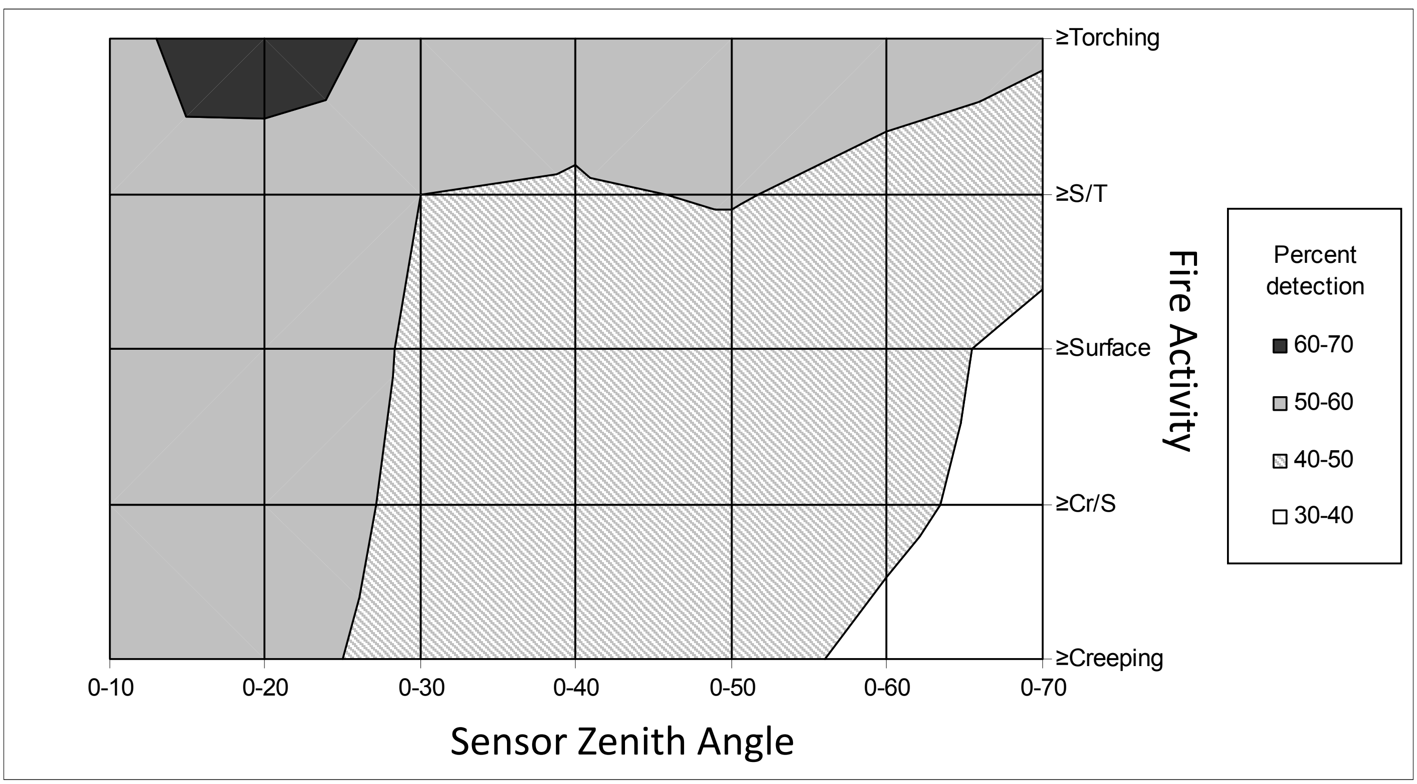


Figure 3: The percent detection for observations with the different combinations of values for *sensor view angle* and *fire activity*. The darkest color indicates the values of *sensor zenith* and *fire activity* where observations were detected 60 to 70 % of the time, decreasing to white which are observations that were detected 30 to 40% of the time.

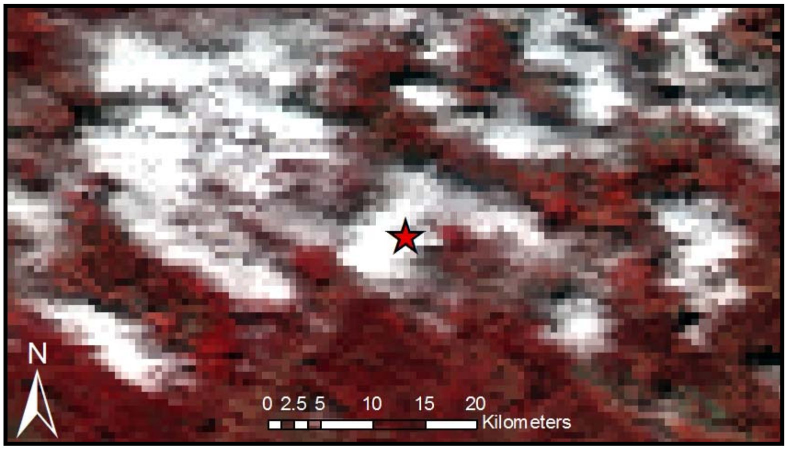


Figure 4: NIR image of the Barker fire on 8/20/2008. The star is the location of the active fire observation; clouds are shown in white. The cloud over the fire is likely to have caused the fire activity observed on the ground to be missed by MODIS.

APPENDIX A

Welcome to…

Heather Heward's Masters Project

Remote Sensing of Wildland Fire Behavior and Effects: comparing MODIS and the Hazard Mapping System (HMS) to on-the-ground fire observations

Thank you for participating!

Please read on to learn what this is all about and how to take your observations

Project support comes from the University of Idaho's fire research program
http://www.cnr.uidaho.edu/fwp/

and from FRAMES
http://frames.nbii.gov/

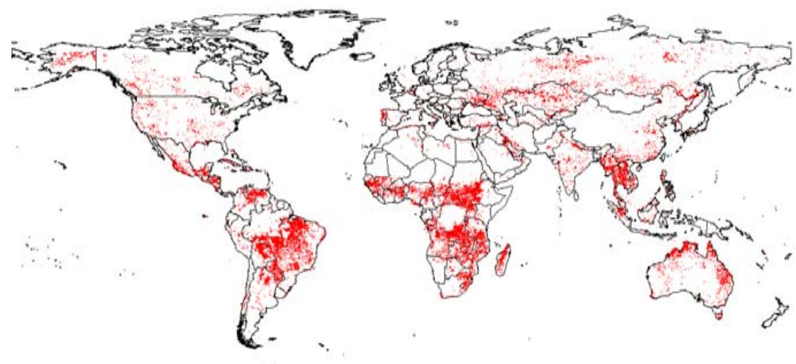
Brief overview of the project

- There are pictures being taken of the earth all the time from various satellites
- We want to see how good one of these satellites is at taking pictures of active fires.
- To do this we will compare the pictures from the satellite to real observations of fire that you will take.
- If the information the satellite generates matches up with the ground observations you have taken, perhaps we can monitor fires with satellites.

Here is a more detailed description

Motivation: Using remote sensing to observe fires is very exciting. The beauty of remote sensing is that, when validated by on-the-ground observations, it can be used to get consistent information over large areas with relative ease.

Observing fires using remote sensing is a growing area of interest since there are about 124 million acres burned annually around the world (see figure below)



http://www.universetoday.com/am/publish/online_map_forest_fires.html

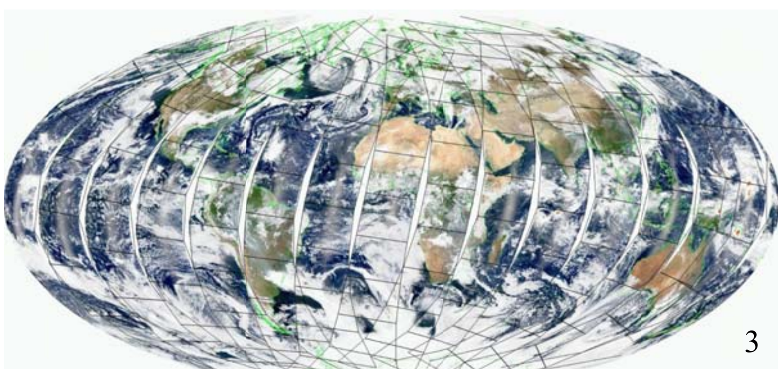
As you can imagine, all this fire impacts vegetation structure, carbon emissions and other things people care about.

If we are able to distinguish between high intensity and low intensity fires, we can then make assumptions about the active-fire characteristics and post-fire effects. With this validation, remote sensing could be used to help monitor fires in remote areas which would increase the safety and effectiveness of firefighters.

There are many tools that are currently being used to observe these fires, but most are poorly validated. This is where **<u>you</u>** come in.

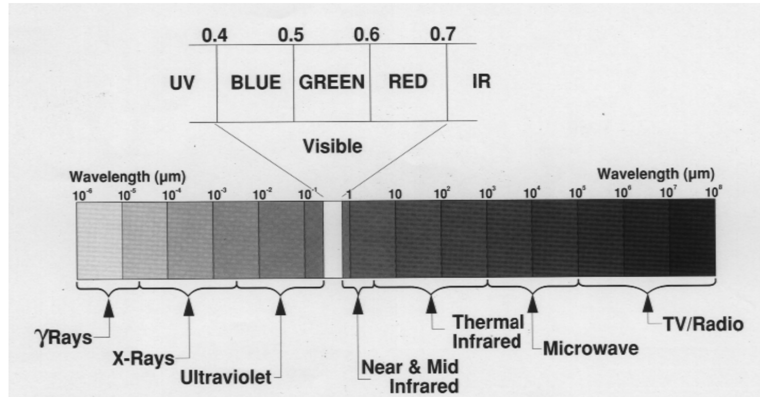
MODIS: MODIS stands for Moderate Resolution Imaging Spectroradiometer. It is currently used to map fire size and extent. We think it might be helpful in telling us where fires are burning intensely and where they are not, so we want to know if it can consistently tell the difference between high and low intensity fires in the satellite image. Here are some of the specs of MODIS.

<u>Temporal resolution:</u> Each day, there are 3-4 usable images produced from MODIS. These images are taken at about the same time each day. This is why it is important to take your observations at the times indicated in the active fire instructions



http://www-loa.univ lille1.fr/Hdf/NewDec2003/images/Browse1kmsm.gif

<u>Spectral resolution:</u> This refers to the types of energy the sensor is sensitive to. MODIS is multispectral, which means that it collects information from all sorts of different areas in the electromagnetic spectrum (below). We are going to be using the thermal bands since that is where fire puts out the most energy. We think that energy being released from these bands will be related to intensity.



http://casde.unl.edu/tutorial/rs-intro/spectrum/index.php

<u>Spatial resolution:</u> One MODIS pixel covers 1 km^2 (250 acres) of area on the ground. This means that all of the information in that pixel is given one value. There are, however, techniques for getting more information out of one pixel.

Hazard Mapping System (HMS): HMS uses a handful of other sensors that also look at fire; these sensors are used to produce the active fire product found on http://geomac.usgs.gov/ (Check it out it is really cool!). This site shows the active fire perimeter of most large fires and also overlays the fire perimeter produced by the IMT. The data that you will collect will help to validate the satellites that create this product.

Why I need your help? You are the resources on the ground that see the fire activity and interact with the fuels. Observing fire behavior is something that happens constantly when you are on the fireline or serving as a lookout; I am asking you to document these changes in fire behavior so that I can also know.

University of Idaho: The University is a leader in Fire Ecology, Management and Technology. There are many faculty and students involved in research related to fire at this time and we are in the process of hiring a new faculty member to teach fire behavior, combustion and fuels for the nation's first B.S. in Fire Science. UofI also teaches courses via Internet and workshops to help people meet GS-401 qualifications. http://401series.net/.

Heather's personal history:

Hometown: Born in a shack in Port Angeles, WA.

Education: In May of 2006, I graduated from the UofI with a Bachelors of Science (B.S.) in Natural Resources Ecology and a minor in Fire Ecology and Management. I am currently working on my Masters of Science at the UofI in the Forest Resources Department and will be finished in the spring of 2009.

Work Experience:

2002 – Engine in Port Angeles, WA (not many fires in a temperate rain forest)
2003 and 2004 – type 1.5 hand crew in Entiat, WA
2005 - Calaveras FUM hooked me into fire use
2006 – Krassel heli-rappel crew on the Payette NF
2007 to Present– Bandelier FUM

Interests: I love to sing and sew and usually have an embroidery kit with me on fires. As some of you know, I also love cake. Carrot cake with cream cheese frosting, Yum!

Brain Teasers! (answers on page 10)

1. What gets wetter and wetter the more it dries?
2. You throw away the outside and cook the inside. Then you eat the outside and throw away the inside. What did you eat?
3. What goes up and down the stairs without moving?
4. What can you catch but not throw?
5. I'm where yesterday follows today, and tomorrow's in the middle. What am I?
6. What goes around the world but stays in a corner?
7. Give me food, and I will live; give me water, and I will die. What am I?
8. The man who invented it doesn't want it. The man who bought it doesn't need it. The man who needs it doesn't know it. What is it?
9. Throw it off the highest building, and I'll not break. But put me in the ocean, and I will. What am I?
10. What can run but never walks, has a mouth but never talks, has a head but never weeps, has a bed but never sleeps?
11. No sooner spoken than broken. What is it?
12. I'm the part of the bird that's not in the sky. I can swim in the ocean and yet remain dry. What am I?
13. I am mother and father, but never birth or nurse. I'm rarely still, but I never wander. What am I?
14. I went into the woods and got it. I sat down to seek it. I brought it home with me because I couldn't find it. What is it?
15. I am weightless, but you can see me. Put me in a bucket, and I'll make it lighter. What am I?
16. I'm light as a feather, yet the strongest man can't hold me for much more than a minute. What am I?
17. I am the black child of a white father, a wingless bird, flying even to the clouds of heaven. I give birth to tears of mourning in pupils that meet me, even though there is no cause for grief, and at once on my birth I am dissolved into air. What am I?

How to Take Active Fire Observations

Please take these observations **<u>Any time of day or night</u>** on **<u>Any Fire You See,</u>** WFU, RX, AMR, suppression etc.

Fire name: If there are multiple fires, just be as specific as possible

State and closest town: This was a problem that I did not foresee last summer; a general idea of where you are will really help.

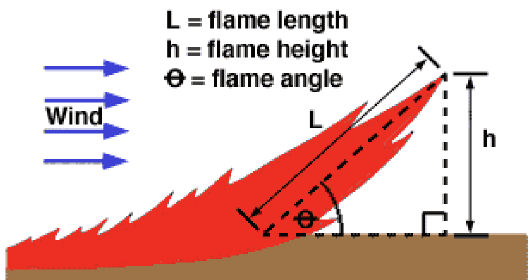
Distance from fire: To get an idea of how you are seeing the fire

Aspect: This in important since there could be situations when the satellite is looking at the fire from an angle and it gets blocked by the hill side.

Time: Previously we were only looking at MODIS, now we are going to be using these observations for several satellites that look at the earth at various times so take observation at <u>Any time of the day or night</u>

Fire Location: Please set your GPS to NAD 83, if you can't do this, please note what datum your GPS is in.
<u>Lat, Long is best</u>, if not just let me know what you used.

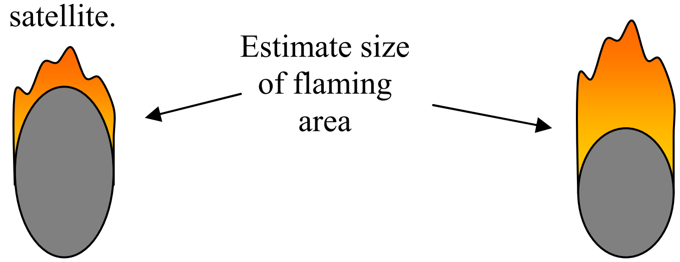
Flame length: Measured along the slant of the flame from the midpoint of its base to the tip



http://www.ffp.csiro.au/nfm/fbm/index.html

Size of flaming area (acres or ft^2): How much area is actively flaming? This is important because we want to know how much energy the fire is emitting.

- Which of these fires is putting out more energy? They may have the same flame length, but one is putting out a lot more energy and will therefore be seen differently by the satellite.

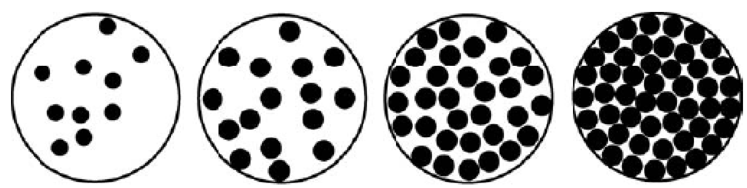


<u>Ex:</u> If you are burning, and you have 3 lighters 10 feet apart and they go 5 chains, the answer to this question is 30ft X 5 Ch.

% Canopy Cover and Type: Again, pretend that you are a satellite looking down at the earth. If there is fire on the ground and the satellites can't see it, it would be good to know at what points the canopy is too thick to see certain flame lengths. The species of tree may also have something to do with it but we will just have to see! Take a picture, it will help me.

- If you aren't right next to the fire, make an educated guess and try to take a representative picture in similar fuels

Use the following examples to help you estimate % cover.



10% 25% 50% 75%

Rate of Spread: If you are in a location where you can physically measure this, do so. If you are too far away, or you don't have time to take the measurement, just make your best educated guess. We are trying to get a better idea of how the fire is behaving**.**

Primary Fire Carrier: What is taking the fire from one place to another? Ex. Pine needles, Duff, logs

Predominant fire movement:
Head: Fire that is moving with the wind
Flanking: Fire that is moving perpendicular to the wind
Backing: Fire that is moving into the wind

If it is Fluctuating put two with a slash and describe it in the notes
Ex. Head/flank

Predominant Fire activity:
Creeping: low flame lengths and rate of spread
Surface: Burning along the surface without significant movement to the overstory, with flame lengths usually below 1 m
Torching: Burning mainly as a surface fire that occasionally ignites the crowns of the trees and shrubs as it advances.
Crowning: Moved from the ground to the forest canopy and runs from top to top of the trees or shrubs.

Again use "/" if more than one are present

Other activity within 1km: Since all the information underneath a MODIS pixel (1km^2) is made into one value, having more fire activity in that area than is being reported in the observation sheets may cause some misleading results. This is important information for quality control.

Comments: Variations in fire activity throughout the time of the observations are always good to know.
*This is the place to give additional information about the kind of activity that is taking place outside of the area you are observing.
- Approximate distance to other activity
- General activity level of that portion of the fire

Camera stuff: Make sure your camera has the right time and make a note of what time zone it is in. With this information I can use the pictures as a mini observation.

Photo: I would love as many pictures and videos as you want to give me of …(in order of importance)
1. Active fire
2. Canopy closure
3. Fire activity outside of observation area
4. Pre and post fire (I love time lapses, so if you are in one spot for a while that would be great!)
5. YOU, I would love to see some pictures of you doing your job, or even better, taking my observations!

Answers to Riddles from Page 6

1.Towel;2.Corn;3.Rug;4.A cold;5.Dictionary;6.Stamp;7.Fire 8.Coffin;9.Tissue;10.River;11.Silence;12.Shadow;13.Tree; 14.Splinter;15.Hole;16.Breathe;17.Smoke

Front

Active Fire Observations

Any time of the day or night
Use extra lines to make multiple observations throughout the burning period
from *one* or a *variety* of locations.

Fire name:	State and closest town:	
Current fire size:	Distance from fire:	
Observer:	Date:	Aspect

	Fire location (Lat Long in NAD 83)	Flame Length (ft)	Size of flaming area (acres, ft2, or Chains)	ROS (ch/hr)	% Canopy Cover and Type	Primary Fire Carrier
Time1						
Time2						
Time3						
Time4						

Back

Pictures: <u>Take Many Pictures!</u> Of…ACTIVE burning, Canopy closure, and if your there; before and after the fire. Organize in Folders on Thumb drive. Make sure time on camera is right or I know how much it's off. Take pictures of other nearby fire activity

<u>Camera time zone:</u> <u>Fire time zone:</u>

[Head] [Flank] [Back]	[Creep] [Surface] [Torching] [Crown]	Other activity within 1KM? y/n	**Comments** Variations in activity (ex. Occasional torching, duration of current flaming activity etc.) Include information about fire activity outside of your immediate area (distance from you, high vs. low intensity, etc.)	Pictures (log number)
				from
				to
				from
				to
				from
				to
				from
				to