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Identifying a suitable combination of classification technique and bandwidth(s) for burned area mapping in tallgrass prairie with MODIS imagery

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Abstract

Prescribed fire is crucial to the ecology and maintenance of tallgrass prairie, and its application affects a variety of human and natural systems. Consequently, maps showing the location and extent of these fires are critical to managing tallgrass prairies in a manner that balances the needs of all stakeholders. Satellite-based optical remote sensing can provide the necessary input for this mapping, but it requires the development mapping methods that are specific to tallgrass prairie. In this research, we devise and test a suitable mapping method by comparing the efficacy of seven combinations of bands and indices from the MODIS sensor using both pixel and object-based classification methods. Due to the relatively small size of many prescribed fires in tallgrass prairie, scenarios based on the 250 m spatial resolution red and NIR bands outperformed those based on the coarser 500 m spatial resolution bands, and a combination of both red and NIR performed better than each 250 m band individually. Object-based classification offered no improvement over the pixel-based classification, and performed poorer in some cases. Our results suggest that mapping burned areas in tallgrass prairie should be done at a minimum of 250 m spatial resolution, should used a pixel-based classification technique, and should use a combination of red and NIR.

Keywords: burned area mapping, MODIS, object-based classification, tallgrass prairie, grasslands

1. Introduction

1.1 Background

1.1.1 The Role of Prescribed Fire in Tallgrass Prairie

Prescribed fire influences sustainability, species composition and richness, and plant community productivity in tallgrass prairies (Knapp and Seastedt, 1998), and it is likely that these grasslands evolved in conjunction with fire (Bragg and Hulbert, 1976). Fire in tallgrass prairies is also closely related to grazing practices (Collins and Steinauer, 1998), nutrient cycling (Hobbs et al., 1991), and the abundance and diversity of wildlife species (Fuhlendorf et al., 2006). Additionally, smoke from burning tallgrass prairie can adversely affect human health within the airsheds of burned areas through the release of chemical compounds and particulate matter (Pope et al., 2002; Radke et al., 2001). Because the stakeholders affected by prescribed burning in tallgrass prairie are numerous and diverse, management decisions should be guided by sound science so that the interests of all parties are addressed objectively and fairly. One important step toward achieving this goal is to develop an accurate method for mapping burned areas in tallgrass prairie.

1.1.2 Burned Area Mapping in Tallgrass Prairie

Typically, satellite imagery is used to map burned areas for several reasons, including its temporal and spectral resolution, its ability to access areas that are inaccessible by other methods, and its cost-effectiveness (Pereira et al., 1997). In fact, a large body of knowledge exists concerning burned area mapping in cover types other than tallgrass prairie, such as forests, savannahs, scrublands, and even semi-arid grasslands.

Often, however, information presented in burn mapping studies from other cover types is not directly applicable to burn mapping in tallgrass prairie. For example, Stroppiana et al. (2002) found that spectral regions that excelled at differentiating between burned and unburned forest could not do so in grasslands, because the differences between burned and unburned areas remain on the landscape much longer in forests. Pereira (2003) provides another example, noting that the major reflectance change in burned woodland savannah is a decrease in NIR, while reflectance in burned grassland decreases across the spectrum.

Although these examples are from wooded and semi-wooded areas, studies from less-wooded savannahs and semi-arid grasslands often fail to provide burn mapping information that is directly applicable to tallgrass prairie. For example, Trigg and Flasse (2000) report that the char signal of a burned savannah area disappears quickly, even in the absence of vegetation regrowth. Cao et al. (2009), examining a semi-arid grassland, also found differentiation between burned and unburned areas difficult in the absence of a char signal, despite the absence of immediate vegetation regrowth. These studies stand in contrast to tallgrass prairies, where burning is typically done during the spring growing season. Consequently, a rapid decrease in the char signal, along with rapidly regrowing vegetation, quickly eliminates the spectral differences on which burned area detection depends (Mohler and Goodin, 2010; Trigg and Flasse, 2000). This has the obvious effect of causing confusion between unburned vegetation and older burned areas (Eva and Lambin, 1998).

Despite the fact that the aforementioned studies cannot be applied directly to burn mapping in tallgrass prairies, they still provide information on which mapping techniques, and which regions of the spectrum, might prove useful for this purpose. Regarding techniques, burned areas have been extensively mapped using both pixel-based and object-based classification methods. Typically, because burned areas are essentially discreet geometric shapes, object-based techniques have outperformed pixel-based techniques (Gitas et al., 2004, 2008; Mitri and Gitas, 2004a, 2004b, 2006, 2008) for this purpose. It should be noted that most studies using object-based classification to map burned areas, including those cited above, were done in forested areas. Nonetheless, many of the technical aspects of these endeavors are applicable to grasslands as well.

Studies in other cover types can also serve as the basis for selecting bands and indices that might be useful for mapping burned areas in tallgrass prairie as well. For example, the middle-infrared burn index (MIRBI) was shown to be useful for differentiating burned from unburned shrub savannah by Trigg and Flasse (2001). It is calculated as

$$\mathrm{MIRBI} = 10(\rho_{\mathrm{LMIR}}) - 9.8(\rho_{\mathrm{SMIR}}) + 2 \qquad (1)$$

where ρ_{LMIR} is the reflectance value of MODIS band 7, and ρ_{SMIR} is the reflectance value of MODIS band 6. Near-infrared (NIR) was shown to be useful for burned area mapping by Lopez-Garcia and Caselles (1991), Koutsias and Karteris (1998), Pereira (1999), Pu and Gong (2004), and Shao and Duncan (2007) in shrubland and forest. The red spectral region also performed well according to Lopez-Garcia and Caselles (1991) in forest, and according to Stroppiana et al. (2002) in savannah. Both NIR and red were useful for differentiating burned from unburned areas in tallgrass prairie according to Mohler and Goodin (2010). Finally, long wave near infrared (LNIR) was found useful for differentiating burned and unburned areas by Li et al. (2004) in forest and by Trigg and Flasse (2000) in savannah.

The objective of this study, therefore, was to identify at classification technique and those spectral bandwidth(s) (and/or the MIRBI index) that could accurately map burned areas in tallgrass prairie. Because past burned area mapping efforts have focused on other cover types, this technique would be the first specifically designed to map burned areas in the tallgrass prairie biome.

1.2 Study Area

The study area was a portion of the northern Flint Hills, Kansas, USA (Fig. 1). The Flint Hills region is the largest extant tract of tallgrass prairie in North America (Knapp and Seastedt, 1998; Kollmorgen and Simonett, 1965). Though the study area is dominated by tallgrass prairie, other cover types such as croplands and woody vegetation can be found, particularly in the floodplains of the area's watercourses. The prairie portions of this study area are dominated by a matrix of tall, warm-season grasses, including *Andropogon gerardii, Schizachyrium scoparium, Sorghastrum nutans,* and *Panicum virgatum* (Freeman, 1998). Non-graminoid forbs and shrubs are often interspersed with the matrix species, and short and mid-sized grasses such as *Bouteloua gracilis* (blue grama), *Bouteloua curtipendula* (sideoats grama), and *Buchloe dactyloides* (buffalograss) are often found in more xeric sites (Freeman, 1998). Typically, burning of the prairie portions of the study area begins in mid-March and ends in mid-May, with the vast majority of burning taking place during the month of April. Insert figure 1 here.

2. Methods

2.1 Data

The satellite imagery classified in this analysis consisted of the first seven bands from the Moderate Resolution Imaging Spectroradiometer (MODIS). These were downloaded through the National Aeronautics and Space Administration's (NASA's) Warehouse Inventory Search Tool (WIST) for four dates in 2008 and three dates in 2010. These particular dates were chosen because they roughly corresponded with Thematic Mapper (TM) scenes that would later be used to evaluate accuracy. MODIS bands 1 and 2 were downloaded at their highest possible resolution of 250 m (MOD09GQ, MYD09GQ). Additionally, bands 1-7 were downloaded at 500 m spatial resolution (MOD09GA, MYD09GA). The specifications for these bands are shown in Table 1. Insert table 1 here.

All MODIS images were converted to TIFF files and georectified to the Universal Transverse Mercator (UTM) system (zone 14) using the MODIS Reprojection Tool (MRT) version 4.0, and subset to include only the study area shown in Figure 1. Because MODIS images could come from either the Aqua (afternoon pass) or Terra (morning pass) satellites, both sometimes provided a clear image on the date in question. In these cases, the image in which the study area was closest to nadir was used, as that allowed for the highest possible spatial resolution. It should be noted that because Aqua passes over the study area in the afternoon, while Terra passes over the study area in the morning, Aqua would likely be the better candidate for burned area mapping, as it will allow the detection more burned area for a given day. However, this research will show that the advantage of an early overpass time is less important than spatial resolution, particularly since burned areas not mapped by Terra on a given day can be capture on a later day with no reduction in accuracy.

TM scenes were used in this study to evaluate the accuracy of the MODIS classifications, as comparison with higher-resolution imagery is a reliable and widely accepted technique for evaluating the accuracy of burned area classifications (Eva and Lambin, 1998). For each of the seven MODIS images mentioned above (4 in 2008 and 3 in 2010), a TM scene that was downloaded through the United States Geological Survey’s (USGS’s) Global Visualization Viewer (GloVis). In all seven cases, the corresponding MODIS and TM scenes were taken within one day of each other. Information for the seven pairs of scenes is given in Table 2. Insert table 2 here.

Ground truth data that showed the extent of several specific burned areas were collected during the 2008 and 2010 burn seasons. These data were used for local classification accuracy assessment. Six burned areas from 2008 were digitized from oblique digital photographs taken by a handheld digital camera while flying over burned areas. Digitization was accomplished by matching burned pastures depicted in the oblique aerial photographs to their boundaries as shown in 1-meter National Aerial Imagery Program (NAIP) color orthophotos from 2008. Typically, features that could be depicted in both photos, such as roads and fences, bordered burned areas, and provided a reliable digitization of burn extent. When this was not the case, or when a pasture area was not completely burned to its fence-line or bordering road, other, more subtle landmarks, such as changes in topography or changes in vegetation were used to interpret the edge of the burned area. Twelve burned areas from 2010 were quantified *in situ* by walking the perimeter of the burned areas with a handheld Global Positioning System (GPS) field computer. The burned areas in 2008 ranged in size from 46 to 744 ha, while those in 2010 ranged in size from 31 to 958 ha (Table 3). Insert table 3 here.

In order to simplify the classification process (to allow for a burned/unburned binary classification), a mask layer was generated that excluded land cover types other than grasslands from the imagery. Masking is common in burned area mapping (e.g., Pereira, 1999; Shao and Duncan, 2007; Stroppiana et al., 2003), and was appropriate here because most prescribed burning is applied to grassland portions of the Flint Hills. The mask was built by excluding pixels of certain values, which tended to represent non-grassland cover types (Table 4). The exact thresholds used were identified through knowledge of spectral responses and trial and error. Importantly, these thresholds were set conservatively. That is, failing to mask non-grassland pixels was more acceptable than accidentally masking grassland pixels. One mask was built for each of the two spatial resolutions (250 m, and 500 m). The masks were built using MODIS images from outside of the burn season (Table 4) in order to avoid masking burned grasslands, which often have similar reflectance values to non-grassland cover types. Though the mask was developed using only imagery from 2008, the stability of land use practices within the study area from year to year allowed the same mask to be used on the 2010 imagery as well. It is also worth mentioning that when using MODIS data, pixels flagged as poor quality due to clouds, smoke, etc. should be masked as well. Insert table 4 here.

2.2 Classification inputs

Classification inputs consisted of single- or multi-band images (hereafter referred to as "scenarios"). Each scenario was composed of one or more different MODIS bands (and/or MIRBI), that have been cited as useful for burned area mapping in various land cover types with various remote sensing systems (see section 1.1.2).

Single-band/index scenarios consisted of NIR, red, LNIR, and MIRBI, and were named Scenario #1, #2, #3, and #4, respectively. The former were available at 250 m spatial resolution, while the latter two were available at a maximum spatial resolution of only 500 m. Multiple band scenarios included one scenario with MIRBI, LNIR, red, and NIR (Scenario #5), and one scenario that used only red and NIR (Scenario #6). This second scenario was constructed because it was the only multiple band scenario possible at 250 m spatial resolution. Finally, a scenario that used all seven MODIS bands at 500 m spatial resolution was created (Scenario #7).

Table 5 shows all scenarios used in this classification and their maximum spatial resolution.

Insert table 5 here.

2.3 Classification

2.3.1 Supervised Minimum Distance Classification

All scenarios for each image date for each of the two years were subjected to a pixel-based classification technique using a minimum distance rule. The minimum distance rule was chosen because it does not require normally distributed data. This was important because only two classes (burned and unburned) represented all land cover types in the study area. Therefore, they had a high probability of being bi or multi-modal (e.g., both older and newer burned areas in the same class).

Training data for each of the two classes (burned areas and unburned areas) were chosen separately in each scenario date. Although selecting the same training data for all dates would have been more consistent, the changing position of burned/unburned areas and clouds through time made this approach impossible, although training data selected for a certain date were used in every scenario from that date. It should also be noted that different training data were used for each of the two spatial resolutions. When both recent and older burned areas were visible, both were used as training data for burned areas. Unburned training data were only selected from grassland areas, though unburned examples of other cover types sometimes escaped the masking process.

2.3.2 Object-Based Classification

In addition to the pixel-based technique, an object-based classification technique was applied to each scenario using eCognition 4.0 software. Segmentation was performed using a Fractal Net Evolution Approach (FNEA), where objects were built from individual pixels and merged pairwise until they met the original segmentation input criteria (Baatz et al., 2004; Benz et al., 2004). The three segmentation criteria for this analysis were chosen so that smaller burned areas (even if they were individual pixels) remained as separate objects, rather than be merged with other cover types—possibly unburned areas. This was consistent with a primary rule of object-based classification—to always produce image objects that are as large as possible but as small as necessary to preserve important details (Baatz et al., 2004). Testing and calibration with trial segmentation runs revealed the value of each of the three criteria that provided that provided an optimal segmentation. This first criterion, “scale parameter,” dictates the general size of the objects that will result from the classification. This was set at 60 for all 250 m scenarios, and at 25 for all 500 m scenarios (the values are different due to differing spatial resolutions). The second criterion, “shape factor,” dictates the ratio of geometric to spectral properties used in the segmentation. This was left at the relatively low default value of 0.1 for all images (regardless of spatial resolution), in order to take advantage of the distinct spectral characteristics of burned areas. The final criterion, “compactness/smoothness,” dictates how compact or convoluted the resulting objects will be. To reflect the tendency of burned areas to be neither completely compact nor overly convoluted, the default value of 0.5/0.5 was used for all images.

Each scenario for each image date for each of the two years was classified into one of three classes: burned, unburned, and masked. Due to limitations of the software, the mask was applied directly to the image prior to classification, accounting for the ‘masked’ class. Training data were selected in the same manner as with the pixel-based minimum distance classification, except that objects were chosen rather than pixels. Typically, at least five objects were selected per class to serve as ground-truth data, though this number was higher in most cases. The number of objects selected depended on class and image date, with burned areas usually being relatively rare in earlier images, and unburned areas becoming rarer toward the end of the study period.

One advantage of object-based classification is the ability to classify images based on geometric properties. However, because burned areas cannot be clearly differentiated from tracts of grassland by geometric properties (particularly later in the burn season), object-based classification was used here as a tool with which to avoid the misclassification of individual pixels and small groups of pixels within larger burned areas. For this reason, the classification of the segmented image was performed with a simple standard nearest neighbor scheme without any geometric considerations. That is, the advantages of classifying objects in this study were realized at the segmentation step, rather than the classification step.

2.4 Accuracy Assessment

Testing the accuracy of each classification scenario was performed in two ways. First, an error matrix was generated for each classification result by comparing each of the MODIS classifications to it corresponding TM image (Table 2). This was done by randomly generating 300 ground truth points within the boundary of each classification result, and assigning each a ground-truth value based on visual interpretation of the TM images. Points were deleted if they corresponded to masked areas, cloudy areas, cloud shadows, MODIS pixels that were flagged for quality problems, areas outside of the particular TM scene being used, or if they fell in other cover types (usually cropland) that went unmasked. This left between 103 and 125 useable points for each MODIS/TM pair depending on image date (Table 6). Finally, it is worth noting that burned area ground truth points were from both recent and/or older burned areas. Insert table 6 here.

For each class (burned and unburned), producer's accuracy was calculated by dividing the total number of points correctly identified in the classification result by the total number of points assigned to each class by the TM reference data. User's accuracy was calculated for each class by dividing the total number of points correctly identified in the classification result by the total number of points assigned to that cover class by the classification scenario. Overall accuracy was calculated by dividing the number of correctly identified points in both classes by the total number of points sampled. Kappa was estimated according to Congalton et al. (1983):

$$KHAT = N\sum_{i=1}^{k} x_{ii} - \sum_{i=1}^{k}(x_{i+} \times x_{+i}) / N^2 - \sum_{i=1}^{k}(x_{i+} \times x_{+i}) \tag{2}$$

where $KHAT$ is the estimate of Kappa, k is the number of rows in the error matrix, x_{ii} is the number of observations in row i and column i, x_{i+} and x_{+i} are the marginal totals for row i and column i, respectively, and N is the total number of observations.

The second way accuracy was assessed was by comparing the area of the 18 ground-truth burns mentioned in section 2.1 with their area as classified by each scenario. For each of the ground-truth burns, the number of burned pixels (according to the classification results) that had their majority within the boundaries of the ground-truth burned areas was tabulated. From these pixel counts, the area of each ground-truth burn according to the classification results was calculated. This provided a measure of local accuracy to complement the global accuracy assessment provided by the error matrices. It should be noted that because the area calculations were based only on pixels within the boundaries of the ground-truth burns, overestimation could not be detected by this assessment technique.

3. Results and Discussion

3.1 Error Matrix Assessment

Evaluation of the *KHAT* values the seven scenarios revealed how accurately each was able to differentiate burned from unburned areas as the growing season progressed (Table 7). One notable result is the failure of Scenario #4 (MRIBI) to ever record a *KHAT* value of greater than 0.8 (80% accuracy)—the only scenario for which this was the case. The other three 500 m spatial resolution scenarios also performed poorly; none displayed *KHAT* values greater than 0.8 for two consecutive image dates regardless of year or classification type. In contrast, all of the 250 m scenarios were able to do this in multiple cases (Table 7). This means that the 500 m scenarios are more sensitive than the 250 m scenarios to the increasing similarity between burned and unburned areas as regrowth occurs. Although the 500 m scenarios were not expected to perform better than the 250 m scenarios, the degree to which temporal performance seems to decrease as spatial resolution decreases suggests a severe limit to the utility of 500 m and coarser data for mapping burned areas in tallgrass prairie. Furthermore, this performance is poor enough to effectively cancel out any advantages coarser MODIS bands might have, such as being available in a greater variety of wavelengths, and providing useable imagery despite smoke and light cloud cover. These results clearly show that burned area mapping in tallgrass prairie should use imagery with at least 250 m spatial resolution. Insert table 7 here.

Among 500 m scenarios, both types of classification (minimum distance and object-based) performed similarly in both years. The apparent poor performance of the LNIR-containing bands in 2010 compared to 2008 (e.g., *KHAT* values ranging between –0.02 and 0.55) was due to the effects of striping on the LNIR band, which the object-based classification did a better job of negating. When this striping is not present, however, the object-based methods are similar to the pixel-based methods. Among the three 250 m resolution scenarios, however, the minimum distance classification outperformed the object-based classification in most cases (Table 7). The two exceptions to this were Scenario #1 (NIR) and Scenario #6 (red, NIR) in 2010, where *KHAT* values were very similar between classification types. These results suggest that pixel-based classification techniques should be used to map burned areas in tallgrass prairie, as they perform much better than object-based techniques when 250 m spatial resolution imagery is used.

Before evaluating the individual merits of the three 250 m resolution minimum distance scenarios, it is worth noting that their initial *KHAT* values (on April 2, 2008 and April 8, 2010) would be higher than shown in Table 8 under typical burn mapping circumstances (focusing on burned areas less than 2 weeks old). Twice in the April 2, 2008 image and three times in the April 8, 2010 image, ground-truth points representing burned areas fell in older burned areas. In 2008, these burned areas were confirmed to be more than a month old, as they were distinctly visible in a March 1 TM image. In 2010, these burned areas already appeared to be several weeks old in a March 23 TM image based on a visual interpretation, making it likely that they were at least one month old in the April 8 image. It is not surprising, then, that these points did not fall into burned areas according to the classification results from these two early-April dates. Using Scenario #6 as an example, excluding these points raises *KHAT* values from 0.84 to 0.90 in 2008, and from 0.81 to 0.89 in 2010. Deleting these points takes away from the otherwise random ground-truth sample, but it more accurately represents a typical real-world burn mapping situation, since burned area mapping efforts will concentrate on more recent burns, and assume that burned areas older than two weeks will have already been detected in a previous image.

This is especially true considering the twice-daily resolution of MODIS imagery. Although the same revision could be made to the 500 m resolution scenarios, the 250 m scenarios were still more accurate.

If the initial *KHAT* values for the three 250 m scenarios are assumed to be near 0.9 (90% accuracy), it becomes apparent that Scenario #6 (red, NIR) maintains higher *KHAT* values than the other two scenarios throughout the time period of burn recovery (or at least until *KHAT* values for all scenarios drop too far for that scenario to be useful for burned area mapping). This suggests that using MODIS bands 1 (red) and 2 (NIR) in combination will provide the most accurate burned area maps in tallgrass prairie, because they allow burned areas to be detected more accurately and for a longer time after burning. That is, these two bands in combination are less sensitive to the effects of vegetative regrowth, which makes burned and unburned areas appear more and more similar as the study period progresses. It should be noted, however, that even the performance of the 250 m scenarios drops dramatically after several weeks, which means that regrowth on both burned and unburned areas will eventually reach a point where accurate detection is impossible, as both areas will appear spectrally similar. Given this trend, accuracy cannot be assumed to be any better than approximately 90%, even with Scenario #6, if the burned areas being mapped are more than two weeks old.

3.2 Areal Extent Assessment

With this accuracy assessment, the ability of each scenario to account for at least 80% of each ground-truth burned area was examined for the two classification techniques. Specifically, the number of consecutive image dates over which at least 80% of the burned area could be accounted for in the classification result was recorded. Also recorded was the maximum number of days that 80% of each burned area might have been accounted for if imagery with actual daily temporal resolution was available (Table 8). Insert table 8 here

Three 500 m spatial resolution scenarios, including Scenario #3 (LNIR), Scenario #4 (MIRBI), and Scenario #5 (MIRBI, LNIR, NIR, red), performed very poorly regardless of which classification technique was used. Although these three scenarios were usually able to detect the larger burned areas, they consistently failed to detect burned areas under 200 ha in size. This finding is similar to that of the error matrix analysis, were these three scenarios also performed poorly. The other 500 m resolution scenario, #7 (MODIS bands 1-7) performed better than the three scenarios mentioned above with both classification types, but often failed to detect smaller burned areas as well. It is likely that the failure of these 500 m scenarios to detect smaller burned areas is at least partially responsible for their poor performance with the error matrix accuracy assessment. Specifically, the fact that the 500 m scenarios consistently miss smaller burned areas means that they are prone to false negatives, which would cause underestimation of burned areas.

The performance of the 250 m scenarios was similar to that of the error matrix analysis in that they outperformed the 500 m bands. When the object-based technique was used, Scenario #2 (red) performed far poorer than either of the other two 250 m scenarios, which performed similar to each other. However, because the error matrix results suggested that the minimum distance technique was better suited for burned area mapping in tallgrass prairie, the results from this classification technique were of more interest here. When minimum distance was used, Scenario #2 was by far the best performer, though it was the worst-performing 250 m scenario using object-based classification. Of the two remaining scenarios, Scenario # 6 (red, NIR) performed slightly better than Scenario #1 (NIR).

The fact that Scenario #2 (red) performed better than the other two scenarios according to the local accuracy technique seems contradictory to the results from the error matrix analysis. However, the tradeoff for this scenario's ability to detect burned areas longer than NIR-based scenarios is that it classifies actively growing vegetation as burned areas. Therefore, when these areas are present in the image, they are classified as burned areas due to their low red reflectance, leading to false positives. These did not affect the performance of Scenario #2 in the error matrix analysis because only grasslands were used for ground-truth data, and these false positives usually occur in other cover types. In light of this problem, the slight advantage of Scenario #6 over Scenario #1 suggests that, as was the case with the error matrix analysis, classification in tallgrass prairie should use a combination of red and NIR at a spatial resolution of 250 m.

4. Conclusions

This analysis suggests that 250 m is the minimum spatial resolution that should be used for burned area mapping in tallgrass prairie, as coarser resolution failed to detect the smaller burned areas that are plentiful in this biome. This was confirmed not only by low *KHAT* values in the error matrix analysis due to low producer's accuracy (suggesting underestimation of burned areas), but also by the failure of the coarser resolution scenarios to detect smaller ground-truth burned areas that were measured in the field or by oblique digital photography. The drawbacks of spatial resolution coarser than 250 m should be considered whenever small burned areas are likely to be encountered, regardless of cover type. However, because some of the 500 m scenarios performed relatively well for the first image date (when regrowth was minimal), they might be useful in cover types where regrowth is slow. The differences in accuracy between 250 and 500 m resolution should also be considered with regard to burned area mapping continuity, as future sensors must have spatial resolutions considerably better than 500 m in order to accurately map burned areas in tallgrass prairie.

The fact that 250 m resolution must be used for burned area mapping in tallgrass prairie means that only the red and NIR bands of MODIS are likely to produce accurate results. In this analysis, however, the red band produced false positives in cover types other than grasslands, while the NIR could not detect burned areas for as long as a combination of red and NIR. Consequently, burned area mapping in this cover type should use a combination of red and NIR.

This study also concludes that burned area mapping in tallgrass prairie, particularly when using the red and NIR bands, should use a pixel-based classification technique. Object-based classification methods did not improve the results in the case of any 250 m scenario, and adversely affected the results in some cases. This is most likely a product of the large 250 m pixel size, as 30 m and higher resolution imagery is used in most studies where object-based classification outperforms pixel-based methods, including most of those mentioned in section 1.1.2.

In summary, this study found that burned area mapping in tallgrass prairie is best performed using the red and NIR spectral regions, imagery with a spatial resolution of 250 m, and a pixel-based classification technique. This method will map burned areas with an accuracy level of approximately 90% when burned areas are less than two weeks old, after which accuracy levels will steadily decrease as vegetation regrows.

Because this is the first burned area mapping technique tailored specifically to tallgrass prairie, estimates of burned area that it produces will be the only objective, systematic estimates of burned area in the Flint Hills of Kansas and Oklahoma. Consequently, they would be (and already are) sought by a wide variety of individuals, including researchers in a number of fields, government agencies at all levels, extension agents, and ranchers. Based on burned area maps produced by this method, further research will uncover a better understanding of the effects of prescribed fire on tallgrass prairies, and allow for the management of this biome with consideration for the human and natural systems that depend on it.

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