

**Using Remote Sensing to Map and Manage Buffelgrass Infestations in the Tucson
and Santa Catalina Mountains**

Final Report

For

The National Park Service

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Executive Summary

Buffelgrass (*Pennisetum ciliare*) threatens to transform the once relatively fireproof Arizona Upland zone of the Sonoran Desert into a frequently burning savanna by out-competing native species and introducing a grass/fire cycle to the environment (Burquez-Montijo et al. 2002). Successful management requires cost effective mapping and monitoring methods (BSP 2008).

The goal of this project was to assess a variety of remote sensing data sets and image processing techniques for their accuracy in the detection and classification of buffelgrass. This assessment was conducted with the underlying objective of identifying approaches that would be practical for the mapping and monitoring of buffelgrass infestations by southern Arizona natural resource managers

We evaluated four readily available remote sensing data products that vary in spatial, temporal, and spectral resolution to identify operational methods for mapping and monitoring buffelgrass. The imagery evaluated includes 1-ft color aerial photography; 1-m color-infrared digital orthophoto quarter quads (DOQQs); 30-m Landsat imagery, which has 6 reflective bands; and ASTER imagery, which has three 15m color/near-infrared bands and six 30m shortwave-infrared bands. We compared manual interpretation (heads-up digitizing) with an automated classification (maximum likelihood) of the high resolution imagery and evaluated automated classifications of the four types of imagery for discrimination of buffelgrass. We performed classifications of each data set with and without topographic information and compared classifications of the 1-ft and 1-m imagery that included incorporation of spatial/textural information. To assess the potential of multi-date classification for detecting buffelgrass, we compared six classifications of multi-date imagery composed of a dry and a wet season pair.

The study area was a 518-hectare region in the Santa Catalina Mountains where all four types of imagery were available at no cost. The imagery considered is widely available over southern Arizona, but past imagery acquisitions have been limited in scope.

Our main findings were:

- High-resolution imagery was the best imagery overall for classification. Classification accuracy was 85% using visual interpretation and 61% using a maximum likelihood classification algorithm.
- Heads-up digitizing was the most effective method for identifying buffelgrass in the high-resolution imagery, resulting in a producer's accuracy of 85% and a user's accuracy of 79%.
- Heads-up digitizing was only possible using the 1-ft resolution color aerial photography, although 1-m imagery with color-infrared could be effective if acquired during the growing season.

- Multi-date analysis of multispectral satellite imagery correctly identified large patches of buffelgrass, but single date classification did not discriminate between buffelgrass and native vegetation or bare ground.
- Including topography (aspect and slope) increased the accuracy of all digital classifications, helping to discriminate between buffelgrass on south-facing slopes and shrubby or herbaceous material on north-facing slopes.
- Buffelgrass is most spectrally distinct early in the summer monsoon season before native vegetation has fully leafed out and in the early fall, after senescence.
- Spatial/texture analysis did not increase the accuracy of automated classification results at the 1-ft or 1-m resolution.
- Incorporating more than two dates has potential for discriminating buffelgrass, but misregistration errors are compounded in high spatial resolution multi-date image stacks.

Using PAG imagery, a GIS specialist who was previously unfamiliar with buffelgrass successfully identified 85% of buffelgrass through heads-up digitizing after just two hours of training to recognize buffelgrass. Therefore, heads-up digitizing is a recommended method for mapping buffelgrass in areas for which high spatial resolution imagery is available.

The most distinguishing data set used in this study was obtained from the Pima Association of Governments (PAG), which purchases digital images for the greater Tucson metro and surrounding areas once every two to four years. These images are purchased through a bulk purchasing agreement in which multiple agencies participate. We recommend that Coronado National Forest and Saguaro National Park join PAG in expanding the footprint of this periodic purchase to include lands invaded by or susceptible to invasion by buffelgrass. Heads-up digitizing using this imagery is recommended for operational monitoring of buffelgrass. Because the texture of buffelgrass is relatively easy to recognize by a briefly trained individual and the volume of imagery to be scanned is so great, incorporation of citizen volunteers in this process is also encouraged. This technique can be used to rectify spatial errors incurred during aerial mapping, providing greater spatial accuracy to broad scale mapping by helicopter mapping methods being evaluated by local land management agencies.

Background

Buffelgrass has invaded large areas of the Sonoran Desert and threatens ecosystem transformation by introducing a grass/fire cycle that devastates native ecosystems (Burquez-Montijo et al. 2002; Yetman 1994). The Arizona Upland—the northernmost zone of the Sonoran Desert—faces dramatic consequences after fire is introduced into the system. Ecosystem dominants saguaros (*Carnegiea gigantea*) and palo verdes (*Parkinsonia microphylla* and *P. florida*) are particularly vulnerable to fire, experiencing high mortality and slow post-fire recovery (Alford et al. 2005; McLaughlin & Bowers 1982; Narog & Wilson 2005). Infrequent periodic recruitment and slow growth suggests

that even a fire return interval of 30 years would be enough to exterminate the saguaro from the landscape (McAuliffe 1995).

The threat of this ecosystem transformation by buffelgrass has unified land managers, business leaders, and elected officials in Southern Arizona, which has led to the development of the Buffelgrass Strategic Plan (BSP) (Rogstad 2008). The BSP, which is designed to direct regional strategic planning and coordination for buffelgrass control and mitigation efforts, provides recommendations for management objectives and research needs. Central to successful invasive species management is an effective mapping and monitoring program, of which remote sensing may be an important component. Of the top eight knowledge gaps identified by the BSP, investigating the use of remote sensing as a tool for mapping and monitoring is listed as #5. The eight knowledge gaps are listed in Appendix A. This paper addresses this particular knowledge gap: “The use of remote sensing to map and monitor buffelgrass.”

Use of remote sensing to map and monitor buffelgrass

Considerable effort has focused on identifying the appropriate spatial, spectral, and temporal resolution for detecting invasive species, including invasive grasses, though specific efforts concerning buffelgrass have been more limited. While a few efforts have successfully detected buffelgrass pastures (e.g. Franklin et al. 2006), detecting small infestations remains a significant challenge, particularly in heterogeneous landscapes such as those found in the Arizona Upland. This is problematic because invasive spread is very sensitive to small, remote infestations; these nascent foci play a disproportionately important role in the rate of spread and infilling of available habitats (Moody & Mack 1988). Thus, lowering the detection threshold is critical in order to manage biological invasions.

Technology

Remote sensing studies of invasive species have utilized imagery with a) high spatial resolution (e.g., aerial photography), b) high spectral resolution (e.g., AVIRIS), c) high temporal resolution (e.g., MODIS, AVHRR), or some combination thereof (e.g., Landsat multitemporal studies). Economic and engineering constraints ensure that spectral, temporal, and spatial resolution cannot be maximized at the same time, so finding an optimal combination is required to raise the probability of detecting small populations.

Aerial photography has been the most commonly used remote sensing product for detecting landscape change for natural resource management, primarily because lower costs in either acquisition or for the expertise required for processing. Aerial photography has also been available much longer than products-derived from satellite sensors, which is important for longer-term change detection. Its use is most appropriate when distinguishing features of strong visual contrast. In such cases, historical aerial photographs have been used to reconstruct vegetation change over multiple decades (Asner et al. 2003; Mast et al. 1997; Williams et al. 1987). Textural clues such as shadows and roughness may aid interpretation, but most texture-based classification is limited to neighborhood statistics (e.g., variance). The addition of a near-infrared band to the sensor can help distinguish dense vegetation, sparse vegetation, bare soil, and litter. Arid landscapes, characterized by low cover and long periods of dormancy, present

phenological constraints and challenges in distinguishing these cover types. Aerial photography is usually commissioned during dry periods when atmospheric conditions are most favorable, which unfortunately is also when most dryland vegetation is photosynthetically inactive. The availability of aerial photography is limited by price, which constrains the timing and extent of imagery for invasive species studies. However many urban areas contract aerial photography for regional planning, thus the costs can be shared across multiple applications and departments.

Multispectral sensors sample reflected radiation in numerous increments in the visible (blue, green, red), near, shortwave (SWIR), and thermal infrared (TIR) wavelengths. For example, Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+), have bands roughly centered at 480, 560, 660, 783, 1650, and 2210 nm with a spatial resolution of 30 meters. ETM+ has an additional 15-m panchromatic band while both sensors have thermal bands as well. Bernthal et al. (2004) mapped *Phalaris arundinacea* in coastal wetlands using Landsat-7 Enhanced Thematic Mapper Plus (ETM+), resulting in an 89% accuracy for dense levels of infestation after masking out areas deemed unsuitable. Peterson (2005) found a 0.71 correlation between modeled *Bromus tectorum* cover from multi-date Landsat imagery and plot-based measurements of percent *B. tectorum* cover. Success at classifying invasive species using Landsat has been limited to large and/or dense infestations, suggesting that, although additional spectral information is useful for distinguishing species or functional types, spatial resolution is limiting. An additional benefit to Landsat is its temporal resolution.

Sensors with high temporal resolution can provide multiple scenes within a season in order to detect spectral changes due to phenology (Blair and Baumgardner 1977). Multi-temporal image data have been used to identify Broom snakeweed (*Gutierrezia sarothrae*) and cheatgrass (*Bromus tectorum*) (Peters et al. 1992; Ustin et al. 2005). Cheatgrass has been identified using multirate AVHRR, Landsat, and AVIRIS imagery, suggesting that this invasive grass is easily distinguishable from native vegetation. Based on its phenology, Bradley and Mustard (2005) showed that increased cheatgrass productivity in wet years makes it distinguishable using NDVI from 1km AVHRR in the Great Basin.

Attempts to specifically identify buffelgrass via remote sensing have not been as fruitful. Franklin et al. (2005) identified buffelgrass pastures in Sonora, Mexico based on pasture boundaries in Landsat imagery validated with low altitude overflights. On the other hand, Brenner (2009) found delineation of pasture boundaries in Landsat imagery possible using image segmentation techniques but found spectral classification ambiguous. If remote sensing of buffelgrass in disturbed areas of Mexico is difficult to discern, similar attempts in natural areas will be more challenging. The highly disturbed and man-made homogeneity of Sonoran buffelgrass pastures in Mexico contrasts sharply with the relatively undisturbed heterogeneous natural habitats of southern Arizona, where buffelgrass is increasingly invasive.

In this study, we will compare high spatial resolution aerial photography (available from Pima Association of Governments, or PAG, and acquired in summer, 2005), USGS DOQQs (from the NAIP program in 2005), ASTER satellite data, and Landsat TM

satellite data. The PAG imagery has 0.33-meter spatial resolution, 3 true-color bands, and is available for urban areas every 2 to 4 years since 1998. The USGS DOQQs are high spatial resolution orthorectified aerial photographs with 1-meter spatial resolution, 3 color bands plus 1 NIR band, and available statewide every 2 to 8 years since 1996. The set we have used was acquired in the summer of 2005. ASTER satellite image data has 2 true-color bands at 15-m, 1 NIR band at 15-m, and 6 SWIR bands at 30-m spatial resolution and is available up to 16 days apart, but is intermittently available since its launch in 2000. Landsat TM satellite image data has 30-m spatial resolution with 3 true-color bands, 1 NIR band, and 2 SWIR bands, and is available every 16 days since 1985.

Classification methods

Classification methods fall into two categories: supervised and unsupervised. In supervised classifications, a set of known reflectances (either in the image or from a library of reflectance values) are used to group pixels in a remotely sensed image into user-defined classes by comparing distances to reference values in spectral space. In unsupervised classifications, the image is segmented into a number of spectrally-distinct classes. In order to assign meaning to the unsupervised classes, an individual must identify each class by comparing them to known infestations on the ground, and often merging a number of classes together. Once the classes are constructed, either via a supervised or unsupervised method, the pixels are assigned using a classifier.

Classifiers can be as simple as the minimum distance to the class mean or can utilize group statistics (mean, variance, probability distribution function) to assign pixels to classes. The Gaussian maximum likelihood classifier assumes a Gaussian distribution within each class and utilizes mean and variance to calculate the probability each pixel would be assigned to each class (Schott 1997). “Cluster busting techniques” can be used to split classes that are not separable by the first order classifier (Narumalani 1997).

In this study, we compared high spatial resolution imagery with multi-date multispectral imagery based on its ability to distinguish buffelgrass from native vegetation. The high-resolution data came from two sources: 1-ft true-color images obtained from Pima Association of Governments (PAG) and 1-m DOQQs with 4 bands (3 visible plus near-infrared). Multi-date images were used to capture two phenological states of buffelgrass: senesced and green and were acquired using Landsat TM and ASTER sensors. Like Landsat TM, ASTER is a multispectral sensor but contains an additional 4 bands in the shortwave infrared (SWIR) and does not contain a blue band. ASTER green, red, and NIR bands have a spatial resolution of 15m and its six SWIR bands have a resolution of 30m.

Ancillary data

In remote sensing, the term “ancillary data” is often used to signify non-imagery datasets that, when integrated with image processing and/or classification steps, can enhance the accuracy of detection and classification (Hutchinson 1982). Commonly used complements of spectral-based classification of vegetation are datasets of features which drive vegetation patterns. For example, in the northern Sonoran Desert, soil texture, the underlying substrate, and topography have been demonstrated to be biogeographically associated with vegetation patterns (e.g., Parker 1991). Pure spectral-based classifiers

ignore spatial pattern, so image texture is often used to provide spatial information for the classifier to address the contextual features associated with the information derived from blocks of pictorial data surrounding the area being analyzed (Haralick et al. 1973). Neighborhood variance provides a measure of spatial heterogeneity, but other focal functions (mean, variance, range, skew, kurtosis) can be used and the neighborhood can range in size and shape. Topography is often included in classifications because it provides additional information about microsite characteristics. Aspect and slope affect the radiation budget at a pixel while elevation serves as a proxy for a number of climatological factors, including temperature and orographic precipitation. We utilized USGS digital elevation models to produce slope and aspect layers to be included in our classifications, allowing us to contrast the spectral-based classification with classifications including topography.

Methods

Image acquisition

We acquired image data that varies in spatial, temporal, and spectral resolution within the Arizona Upland in southeast Arizona. One-quarter meter spatial resolution, 3-band (true color) image from the Pima Association of Governments (PAG) represents the highest spatial resolution data available and is limited to the urban area surrounding Tucson, AZ and was acquired June 2005. One-meter digital orthophoto quarter quads (DOQQs) from June, 2007, includes 3 true color bands and 1 near-infrared (NIR) band. ASTER satellite data features 2 visible and 2 NIR bands with 15-meter resolution as well as 6 short-wave infrared (SWIR) bands with 30-meter resolution. ASTER data for this region is available during multiple dates in 2004, 2005, 2006, and 2007, but precise overlap between images taken at different times of the year limits our scene selection to three dates: 4/22/2006, 7/15/2006, 11/08/2006. In contrast, Landsat data has full coverage of the study area every 16 days (when cloud-free) and features 6 reflectance bands (3 visible, 1 NIR, and 2 SWIR) at 30-meter resolution. A scene from August 31, 2006 was used to capture full summer green-up. All scenes were geometrically rectified to match the DOQQ.

Study area selection

The area of interest for this study is the intersection of all five data types and consists of two sections (518 hectares) just north of Tucson, AZ, in the foothills of the Santa Catalina Mountains (Figure 1).

Selection of training and validation points

The 0.31 meter PAG imagery was used to heads-up digitize through visual interpretation the locations of our classes of interest: buffelgrass, soil/native vegetation, shrubs, trees, rock, and shadow. We randomly selected one hundred 250 by 250 meter areas within the study area and digitized one polygon of each class within each area. Our approach was to follow a procedure similar to one likely to be encountered in a management setting. Therefore, the digitizing was performed by a remote sensing specialist who had no previous experience with buffelgrass but that was provided a 2-hour training on what to look for on the landscape. Following the digitization, we visited each of the points to validate accuracy of the visual interpretation and digitization of buffelgrass. The correctly

classified pixels were randomly divided into two equal-sized sets of 134 points—one for training and another for validation.

Image analysis

Using the ground-truthed training points (268 total points) from the PAG image, a maximum likelihood supervised classification was performed on each PAG, DOQQ, ASTER, and Landsat TM scene. The high spatial resolution imagery was also combined with topography (elevation, slope, aspect) and image texture (3, 5, 7, and 9-neighbor variance). Classifications with ASTER and Landsat data were paired with classifications using topography. Multi-date stacks of ASTER and Landsat data were also classified with and without topography. The multistack stacks were chosen to capture wet and dry seasonal variation.

Ensemble model

An ensemble model consisting of the average buffelgrass classification for all models was also created in order to locate areas with high probabilities of buffelgrass presence. Each classification of varying spatial, spectral, and temporal resolution from the PAG, DOQQ, ASTER, and Landsat data was transformed into a binary image identifying areas with and without buffelgrass. After adding these binary images together, the resulting ensemble model reflects the probability that a given cell would be classified as buffelgrass.

In order to assess the accuracy of the ensemble model, it was varied along a probability gradient to create a receiver operating characteristics (ROC) curve. The ROC curve is a method for grading binary models for their sensitivity vs. specificity by varying the threshold between 0 and 1. The area under the ROC curve is a metric between 0 and 1 that indicates the total discriminatory power of a model. An Area Under the ROC curve (AUC) of 1.0 reflects perfect discrimination whereas an AUC of 0.5 indicates the model is no better than a random classifier.

Evaluation

Remote sensing accuracy assessment addresses the proportion of pixels that are classified correctly (producer's accuracy) and the proportion of pixels in a given class that belong to that class (user's accuracy). These terms are less intuitive than the terms omission and commission. Omission refers to pixels incorrectly excluded from a particular class and commission refers to pixels incorrectly included in a particular class. Thus, producer's accuracy is the complement of omission error and user's accuracy is the complement of commission error.

We evaluated the omission and commission errors of buffelgrass in each of the eight high spatial resolution stacks and visually assessed the spatial arrangement of the classes to select the best classification of PAG, DOQQ, ASTER/Landsat single scene imagery, and ASTER/Landsat multi-temporal stacks. From these classifications, we selected 50 points from each class for additional ground-truth validation. Ground truth measurements were used to create confusion matrices (a matrix or table that displays statistics for assessing image classification accuracy by showing the degree of misclassification

among classes) (Congalton 1983; Kepner et al 2000). User's accuracy and producer's accuracy for buffelgrass classes were used to assess the relative merits of each set of classification imagery.

Results

Visual interpretation through heads-up digitizing of the PAG imagery was the most accurate method, with a producer's accuracy of 85% and a user's accuracy of 79% (Table 1). Of the automated methods using maximum likelihood (ML), combining the PAG imagery with topographic and textural information had the highest overall accuracy among the PAG classifications, resulting in a producer's and user's accuracies of 68% and 36%.

Buffelgrass was classified using ML in the PAG imagery correctly at 53% of the reference pixels and misclassified as shrub 47% (Figure 2). Of the 55 reference points that intersect classified buffelgrass, 31% were correctly classified while 33% were classified as rock and 35% as shrub. When texture was added, buffelgrass was classified correctly 59% of reference pixels and only misclassified as shrub 3% of the time but misclassified as rock 35% of the time (Figure 3). Of the reference points that intersected classified buffelgrass, 26% were rock and 43% were shrub. In PAG images merged with topography, 46% of buffelgrass reference pixels were correctly classified while 48% were classified as shrub and 6% as rock (Figure 4). Of the reference points classified as buffelgrass, 38% were buffelgrass, 27% were rock, and 35% were tree or shrub. In classified PAG imagery with topography and texture, buffelgrass was correctly identified in 68% of buffelgrass reference pixels (Figure 5). Misclassification of rock was most common (29%) and one pixel was classified as shrub (3%). 37% of the reference points that intersect classified buffelgrass are correctly identified. Shrubs were classified as buffelgrass most often (43%), followed by rock (14%) and tree (6%).

In the DOQQ classification, Buffelgrass was classified correctly at 56% of the buffelgrass reference points (Figure 6). Buffelgrass was also classified as shrub (18%), soil (15%), rock (9%), and tree (3%). Of the 125 reference points classified as buffelgrass, 15% were correct. Shrubs were most often included in this class (40% of reference points), followed by soil (26%), rock (15%), and tree (3%). Results were similar when texture was included: 56% of the buffelgrass reference points were classified correctly (Figure 7). Buffelgrass was also classified as rock (18%), shrub (12%), soil (12%) and tree (3%). 125 reference points were classified as buffelgrass, of which 15% were buffelgrass, 37% were shrub, 28% were soil, 15% were rock, and 5% were tree. Adding topography increased the correctly identified buffelgrass reference points to 70% (Figure 8). The rest of these points were classified as shrub (12%), rock (9%), tree (6%), and soil (3%). Of the 116 reference points classified as buffelgrass, 20% were correct. 37% were actually shrub, 27% were soil, 9% were rock, and 8% were tree. The classification of DOQQ with topography and texture classified 59% of the buffelgrass reference points (Figure 9). The other 41% were classified as rock (18%), shrub (18%), and tree (6%). Of the 110 reference points classified as buffelgrass, 18% were actually buffelgrass. 40% were shrub, 26% were soil, 8% were rock, and 7% were soil.

Buffelgrass was classified correctly at 15% of the buffelgrass reference points in the ASTER (Figure 10) April scene. 76% of the buffelgrass points were classified as rock, 6% as soil, and 3% as tree. Of the 25 reference points that intersect classified buffelgrass, 20% were buffelgrass, 48% were soil, 20% were shrub, and 12% were rock. When texture was added, buffelgrass was correctly classified at 6% of the reference points (Figure 11). Points were classified as tree (85%), soil (6%), and tree (3%). Of the 8 pixels that were classified as buffelgrass, 25% were buffelgrass, 50% were soil, and 25% were shrub.

In the July ASTER scene, buffelgrass was classified correctly at 59% of the buffelgrass reference points (Figure 12). 35% of the reference points were classified as rock, 6% as tree, and 3% as soil. Of the 139 reference points classified as buffelgrass, 14% were buffelgrass, 38% were soil, 29% were shrub, 14% were rock, and 4% were tree. When texture was added, buffelgrass was correctly classified at just 41% of the reference points. 53% of the buffelgrass points were classified as rock and 6% as soil (Figure 13). Of the 60 reference points classified as buffelgrass, 23% were buffelgrass, 33% were soil, 25% were shrub, 12% were tree, and 7% were rock.

Buffelgrass was classified correctly at 35% of the buffelgrass reference points in the ASTER November scene (Figure 14). 32% of the reference points were classified as rock, 21% as tree, and 12% as soil. Of the 47 reference points classified as buffelgrass, 26% were buffelgrass, 34% were shrub, 21% were soil, 17% were rock, and 2% were tree. When texture was added, buffelgrass was correctly classified at just 12% of the reference points (Figure 15). 76% of the buffelgrass points were classified as rock and 12% as tree. Of the 12 reference points classified as buffelgrass, 33% were buffelgrass, 33% were shrub, 17% were rock, and 17% were tree.

In the maximum likelihood classification of the August Landsat TM scene, 44% of the buffelgrass reference points were classified correctly (Figure 16). 30% were classified as rock or soil and 15% as tree or shrub. 14% of the 107 reference points classified as buffelgrass were actually buffelgrass. The others were soil (36%), shrub (32%), rock (12%), and tree (6%). When topography was added to the classification, buffelgrass classification accuracy dropped to 26% (Figure 17). Buffelgrass reference pixels were classified as rock (41%), soil (18%), shrub (12%), and tree (3%). 52 reference points were classified as buffelgrass, of which 17% were correct. The other reference points belonged to shrub (37%), soil (33%), tree (10%), and rock (4%) classes.

The multi-temporal classification involving ASTER scenes from April and July classified 9% of the reference points correctly as buffelgrass but, of the 4 pixels that were classified as buffelgrass, 3 of them were correct (Figure 18). 82% of the buffelgrass reference pixels were identified as bare ground and 9% were classified as tree/shrub. The April+July ML classification that included topography did not classify any buffelgrass pixels (Figure 19). Instead, 97% of the buffelgrass pixels were classified as bare and 3% as tree/shrub.

The multi-temporal classification utilizing the July and November ASTER scenes correctly identified 18% of the buffelgrass reference points (Figure 20). The rest were

classified as bare (76%) and tree/shrub (6%). Of the 16 reference points classified as buffelgrass, 38% were correctly identified as buffelgrass, 38% were incorrectly identified as bare, and 25% were classified as tree/shrub. Adding topography to the multi-temporal stack resulted in a classification with only a single pixel predicted as buffelgrass (Figure 21). While the single pixel was correct, 43 other buffelgrass were incorrectly classified as bare ground (93%) and tree/shrub (5%).

The multi-temporal classification that combined the April ASTER and August Landsat classified 12% of the buffelgrass reference pixels correctly and classified the other 82% as bare ground and 6% as tree/shrub. Of the 10 reference points classified as buffelgrass, 40% were buffelgrass, 40% were tree/shrub and 20% were bare. Adding topography worsened the classification, resulting in 0 pixels being classified as buffelgrass. 97% of the buffelgrass points were classified as bare and 3% as tree/shrub.

The multitemporal classification of the August Landsat TM and November ASTER classified 18% of the buffelgrass reference points correctly and 82% as bare ground. 45% of the 29 reference points classified as buffelgrass were shrub, 34% were tree/shrub, and 21% were actually buffelgrass.

Each classification involving pre-monsoon, monsoon, and post-monsoon imagery did not classify buffelgrass at any reference point. This includes the combinations of April, July, and November ASTER imagery with and without topography as well as the combination of April and November ASTER plus August Landsat TM with and without topography.

The ensemble model (Figure 22) had an area under the ROC curve of 0.78 (Figure 23). There were not any pixels that were correctly identified in all 20 classifications (including the 4 classifications involving three scenes). The maximum number of scenes a pixel was classified as buffelgrass was 13.

Confusion of buffelgrass with trees, shrubs, rocks, and soil, was not consistent between classifications involving different types of imagery and including spatial/texture and/or topography (Figure 24). Buffelgrass reference were classified more consistently as tree/shrub in the high resolution imagery and as rock/bare soil in the higher spectral resolution imagery. Commission of shrub reference points into the classified buffelgrass class consistently varied between 20% and 50%. Inclusion of topography in the multispectral classifications reduced commission of bare ground in every single scene classification while in the same scenes, more buffelgrass was classified as bare ground.

Accuracy of buffelgrass classification was higher at lower spatial resolution, regardless of whether topography or spatial/texture was included (Figure 25). The differences were negligible between 15m ASTER and 30m Landsat, but distinct between 15m ASTER and 1m DOQQ and more pronounced between 1m DOQQ and 0.31m PAG image data.

Discussion and Conclusions

This project was designed to analyze remote sensing data for their ability to be used operationally by southern Arizona's land managers to map and monitor buffelgrass infestations. By limiting our data sources to available satellite imagery (e.g., Landsat TM

and ASTER), the ubiquitous USGS DOQQs, and locally available commercial orthophotography (e.g., PAG imagery), we assessed practical, operational methods for detecting and mapping buffelgrass. We sought to address the importance of spatial resolution vs. spectral vs. temporal resolutions and identify the best timing for image acquisition.

High spatial resolution provides the spatial and contextual information to distinguish buffelgrass in the mixed, heterogeneous landscape of the Arizona Upland, but 15-30m resolution is not sufficient to accurately identify buffelgrass. Even at 1m, classification accuracy was much lower than the 0.31m classification, even with the addition of an NIR band. Additional spectral bands are likely to improve classification, as the comparison of Landsat and ASTER summer monsoon scenes suggest, but not as much as increasing spatial resolution. Even a 3-band true color 0.31m aerial photograph was more discriminating than a 4-band color-infrared 1m, indicating that spatial resolution is the primary factor driving detection success. The discriminability of buffelgrass in true-color imagery is clear, but commission errors including a similarly-colored soil and shrubs are not surprising. Automated filtering using supervised classification of high-resolution color imagery could be used as a first pass to narrow the regions to look for buffelgrass. Heads-up digitizing of buffelgrass is remarkably accurate and can be used to further narrow the areas where buffelgrass can be found.

Visual assessment of the classifications indicate that outlines of the largest infestations were identifiable in the high-resolution PAG imagery (Figure 26, Figure 27, and Figure 28), which is useful for long-term monitoring of known buffelgrass patches, but less useful at discriminating patch shape of small, remote infestations (Figure 29 and Figure 30). This is problematic because small, remote infestations have a disproportionately large effect on the rate of spread and infill. However, visual comparisons of the ensemble classifications and the reference points indicate that large patches (>15m in diameter) were classified by as many models as medium-sized (5-15m in diameter) patches.

Arizona Upland landscapes are heterogeneous landscapes composed of a large diversity of life forms, including columnar cacti, succulent shrubs, trees, sub-shrubs, perennial herbaceous cover, drought-avoidant mosses, and native grasses. Typically, these represent 10-30% cover, leaving the majority of the mineral soil uncovered. Since invading buffelgrass tends to occupy the interstitial spaces between native plants, we expected the spectral signal to show a displacement of bare ground with non-photosynthetic vegetation that would show up in the multispectral imagery—specifically ASTER because of its additional spectral sampling in the SWIR, where the spectral reflectance of soil and nonphotosynthetic vegetation are more distinguishable. However, classification using this imagery was not successful at distinguishing infested areas from non-infested areas.

The nature of biological invasions ensures that small, remote infestations, while harder to detect, remain more important from the standpoint of control and monitoring. In addition, invaders may initially inhabit protected locations under nurse trees or against rock outcrops. The high spatial heterogeneity of the Arizona Highlands hampers our capacity to identify buffelgrass with moderate resolution, high spectral resolution imagery alone,

except in locations where buffelgrass is already dominant. Landsat TM and ASTER, while they could be useful for assessing large, continuous areas of buffelgrass, are less useful at distinguishing buffelgrass at the scale of 15-meters or less, where early detection is vital to successful and efficient management. Additionally, the SWIR sensor on ASTER experienced a permanent failure so future image acquisitions with ASTER will be missing the SWIR bands. From an operational standpoint, ASTER is no longer an option due to the recent failure of these detectors.

This research suggests that PAG imagery (0.33m spatial resolution aerial photography with 3 bands in the visible spectrum), which has been purchased by the county every two to four years for populated areas in and around Tucson starting in 1998, has provided the highest classification accuracy, and this is the best candidate for operational buffelgrass mapping and monitoring in the area covered. PAG Imagery from 2005 was used in this research, but more recent acquisitions are available and future acquisitions are likely. PAG imagery is purchased jointly by many buyers, including Pima County and the City of Tucson. PAG imagery from 2008 is now available and covers much of Saguaro National Park's Rincon Mountain District (Figure 5) but is unavailable for most of the Tucson Mountain District (Figure 6). Participation by Saguaro National Park and Coronado National Forest would allow the footprint of PAG imagery to be expanded to include areas susceptible to buffelgrass invasion adjacent to the current coverage area.

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Tables

Table 1. Combinations of imagery and ancillary data to be analyzed in this study

Imagery	Date	Topography	Texture	Producer's	User's	Accuracy
PAG	6/1/2005			53.1%	30.9%	66.3%
PAG	6/1/2005		X	58.8%	26.0%	63.0%
PAG	6/1/2005	X		45.2%	37.8%	67.9%
PAG	6/1/2005	X	X	67.6%	36.5%	60.9%
DOQQ	6/1/2005			55.9%	15.2%	34.5%
DOQQ	6/1/2005		X	55.9%	15.2%	30.4%
DOQQ	6/1/2005	X		69.7%	19.8%	31.0%
DOQQ	6/1/2005	X	X	58.8%	18.2%	25.6%
ASTER	4/22/2006			14.7%	20.0%	18.5%
ASTER	4/22/2006	X		5.9%	25.0%	18.7%
ASTER	7/18/2006			58.8%	14.4%	16.6%
ASTER	7/18/2006	X		41.2%	23.3%	20.3%
ASTER	11/23/2006			35.3%	25.5%	19.0%
ASTER	11/23/2006	X		11.8%	33.3%	16.9%
LANDSAT	8/27/2005			44.1%	14.0%	22.4%
LANDSAT	8/27/2005	X		26.5%	17.3%	24.0%
ASTER	4/22/2006			8.8%	75.0%	43.8%
ASTER	7/18/2006					
ASTER	4/22/2006			0.0%	#DIV/0!	45.4%
ASTER	7/18/2006	X				
ASTER	7/18/2006			17.6%	37.5%	44.1%
ASTER	11/23/2006					
ASTER	7/18/2006			5.9%	50.0%	46.4%
ASTER	11/23/2006	X				
ASTER	4/22/2006			11.8%	40.0%	45.6%
LANDSAT	8/27/2006					
ASTER	4/22/2006			0.0%	0.0%	45.6%
LANDSAT	8/27/2006	X				
LANDSAT	8/27/2006			17.6%	20.7%	43.0%
ASTER	11/23/2006					
LANDSAT	8/27/2006			2.3%	100.0%	44.6%
ASTER	11/23/2006	X				
ASTER	4/22/2006			0.0%	#DIV/0!	45.4%
ASTER	7/18/2006					
ASTER	11/23/2006					
ASTER	4/22/2006			0.0%	#DIV/0!	44.3%
ASTER	7/18/2006					
ASTER	11/23/2006	X				
ASTER	4/22/2006			0.0%	#DIV/0!	45.6%
LANDSAT	8/27/2006					
ASTER	11/23/2006					
ASTER	4/22/2006			0.0%	#DIV/0!	43.3%
LANDSAT	8/27/2006					
ASTER	11/23/2006	X				

Figures

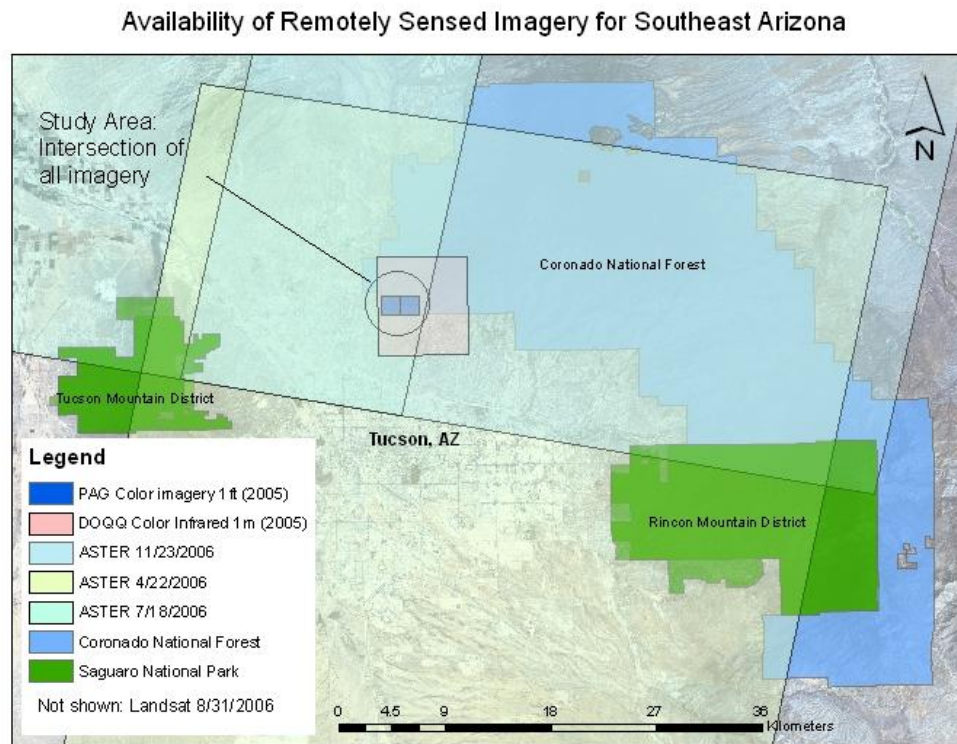


Figure 1. Remote sensing data coverage for southeast Arizona used in this study.

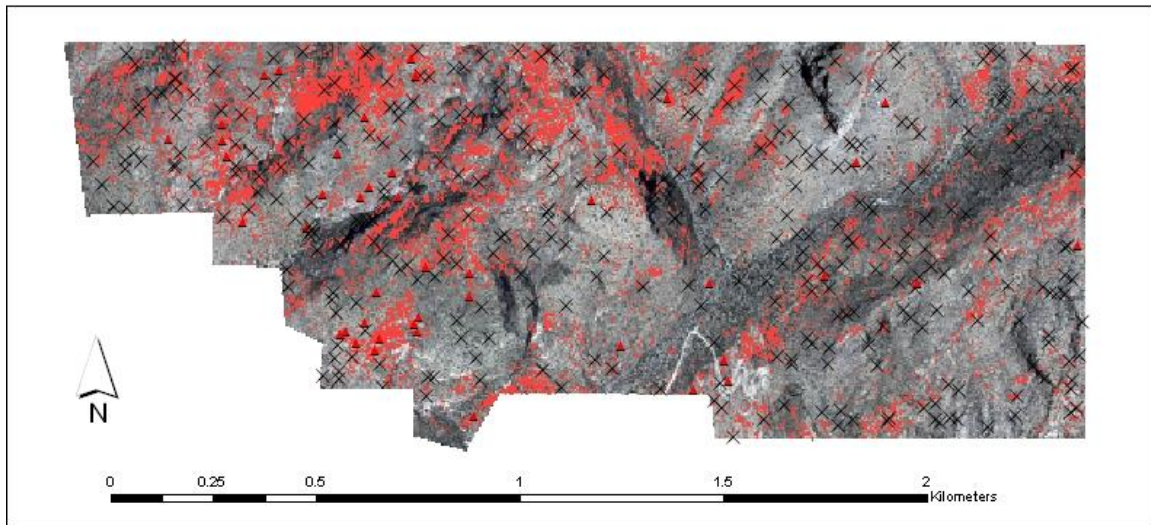


Figure 2. Maximum likelihood classification of PAG imagery. Red areas are classified as buffelgrass. Red triangles represent ground reference points where buffelgrass was found and a black X represents reference points where buffelgrass was not found.

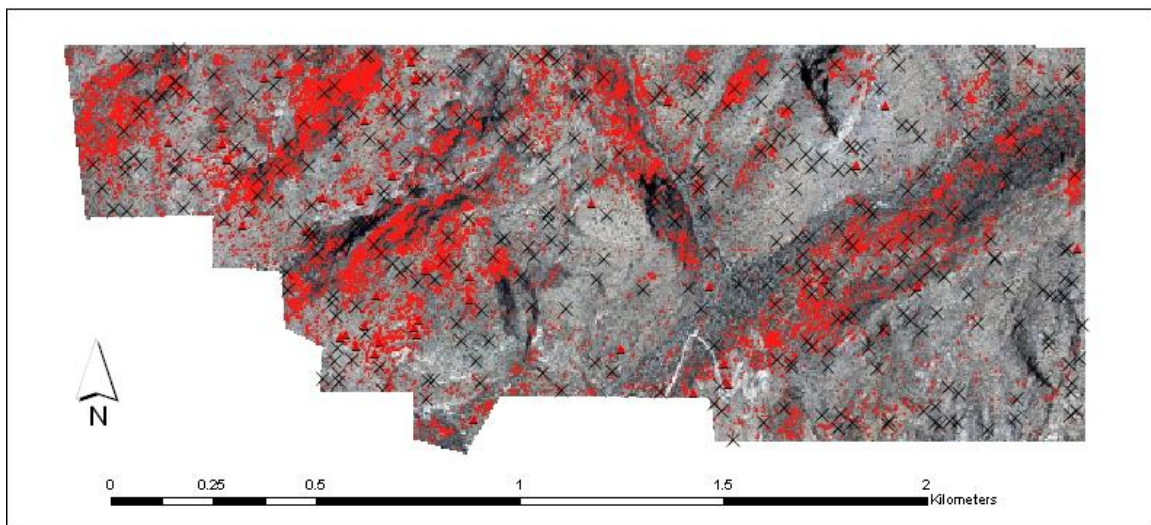


Figure 3. Maximum likelihood classification of PAG imagery with texture. Red areas are classified as buffelgrass. Red triangles represent ground reference points where buffelgrass was found and a black X represents reference points where buffelgrass was not found.

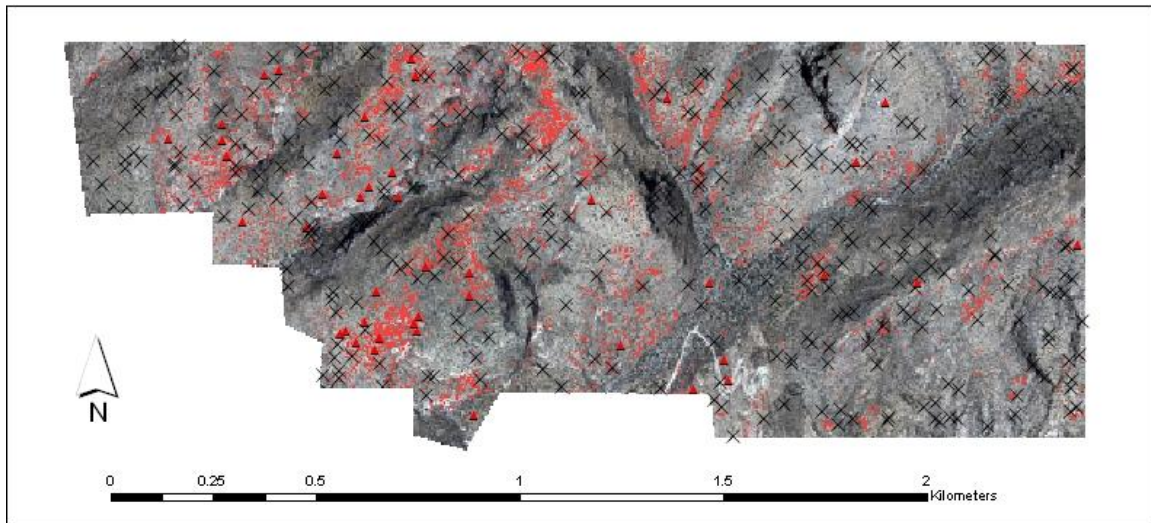


Figure 4. Maximum likelihood classification of PAG imagery with topography. Red areas are classified as buffelgrass. Red triangles represent ground reference points where buffelgrass was found and a black X represents reference points where buffelgrass was not found.

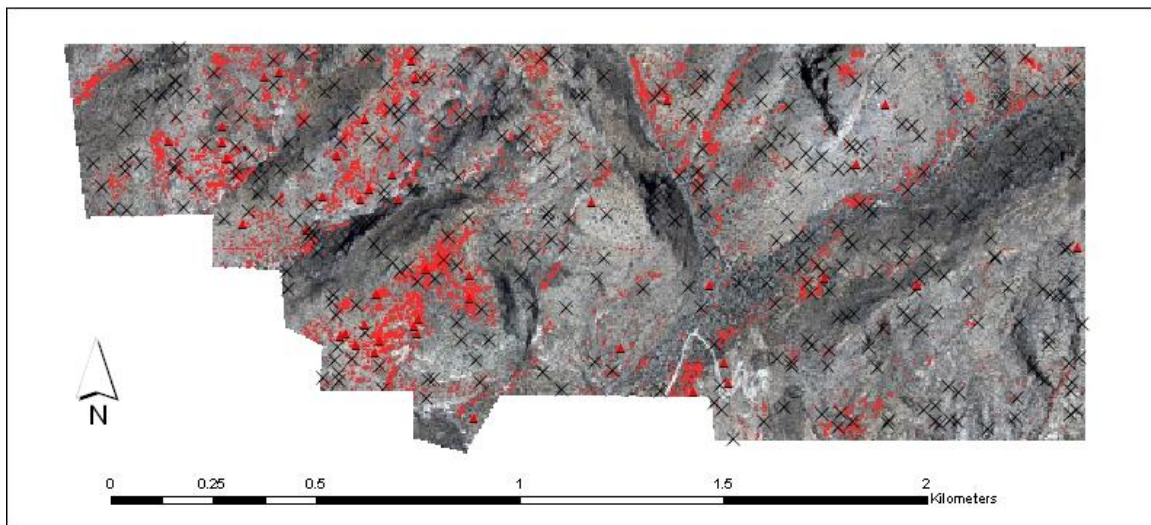


Figure 5. Maximum likelihood classification of PAG imagery with topography and texture. Red areas are classified as buffelgrass. Red triangles represent ground reference points where buffelgrass was found and a black X represents reference points where buffelgrass was not found.

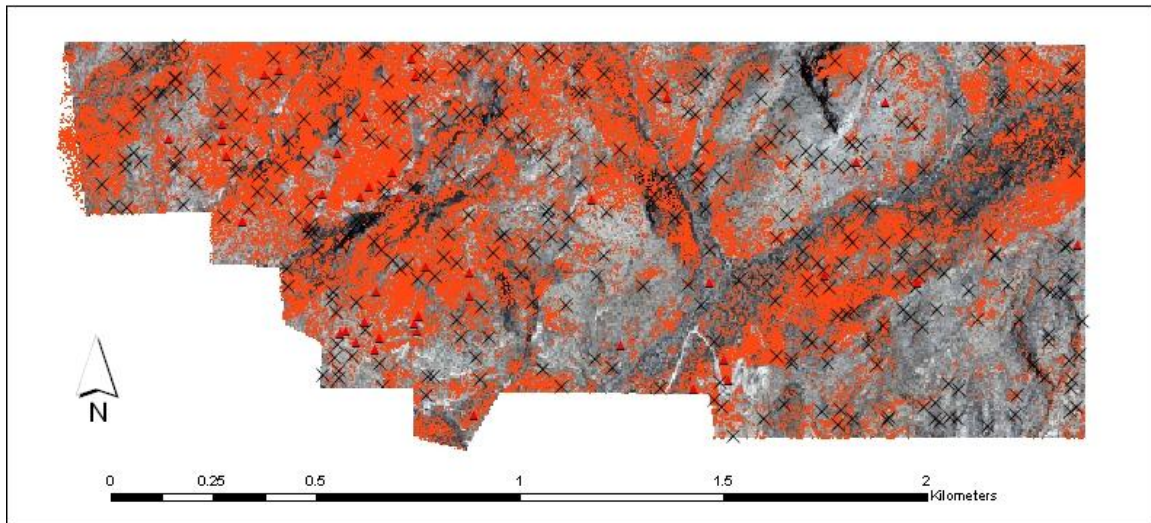


Figure 6. Maximum likelihood classification of DOQQ imagery. Red areas are classified as buffelgrass. Red triangles represent ground reference points where buffelgrass was found and a black X represents reference points where buffelgrass was not found.

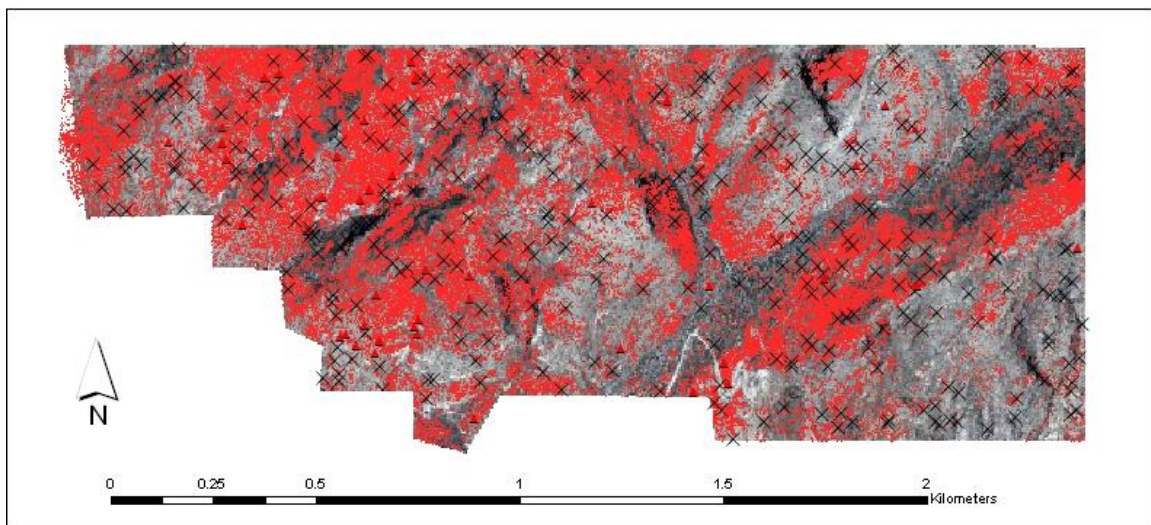


Figure 7. Maximum likelihood classification of DOQQ imagery with texture. Red areas are classified as buffelgrass. Red triangles represent ground reference points where buffelgrass was found and a black X represents reference points where buffelgrass was not found.

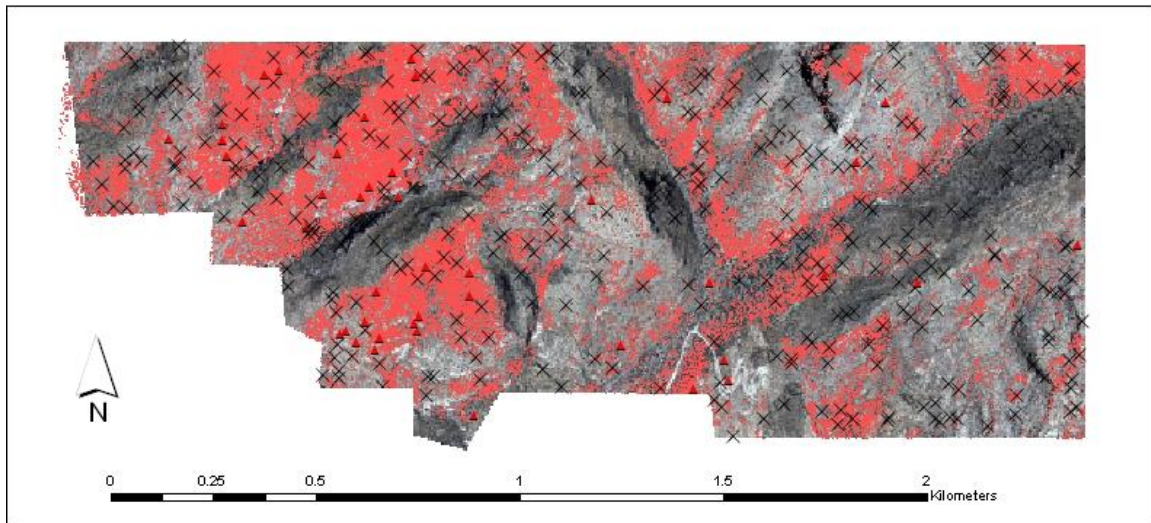


Figure 8. Maximum likelihood classification of DOQQ imagery with topography. Red areas are classified as buffelgrass. Red triangles represent ground reference points where buffelgrass was found and a black X represents reference points where buffelgrass was not found.

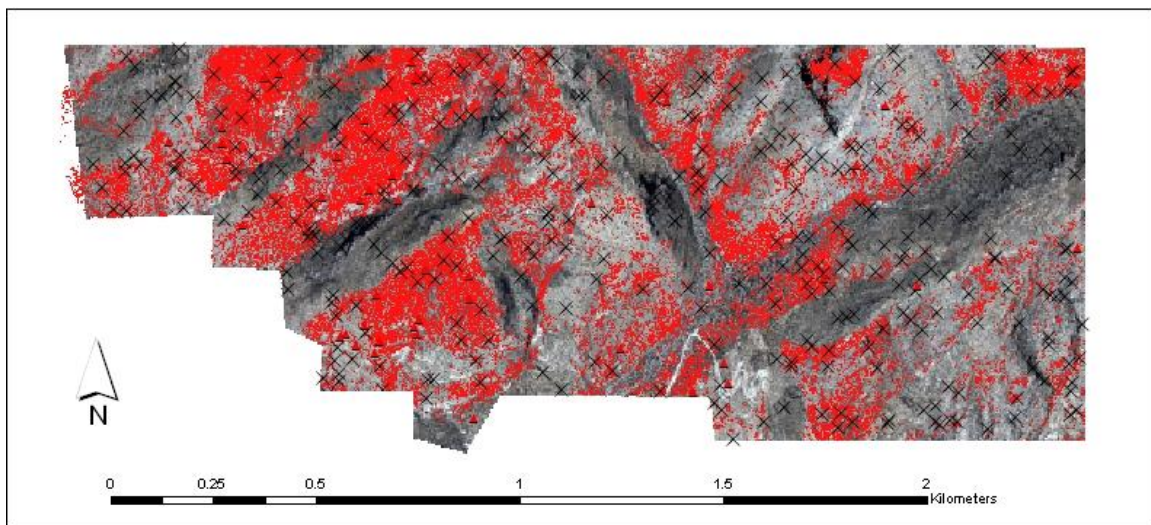


Figure 9. Maximum likelihood classification of DOQQ imagery with topography and texture. Red areas are classified as buffelgrass. Red triangles represent ground reference points where buffelgrass was found and a black X represents reference points where buffelgrass was not found.

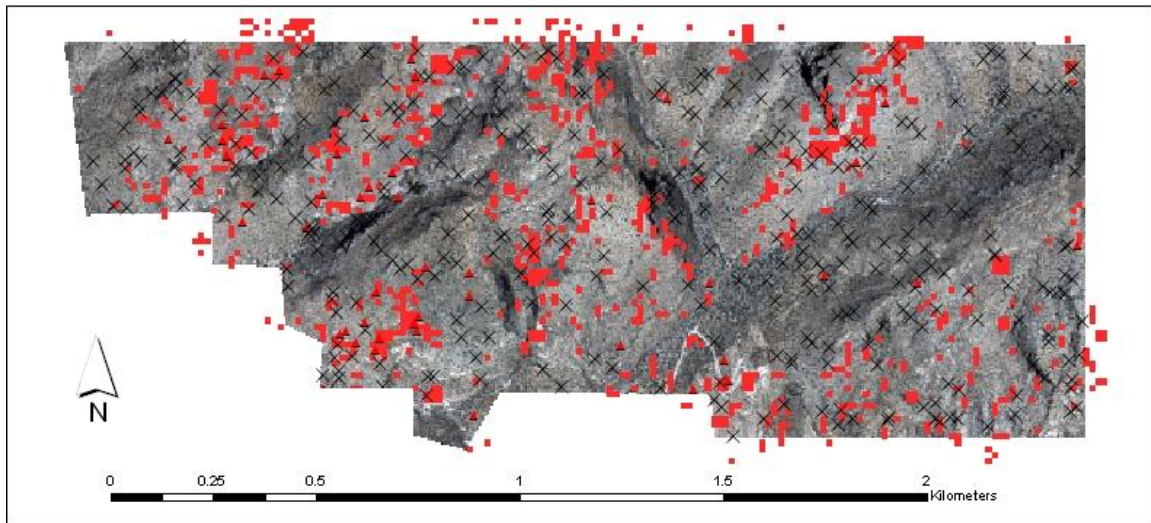


Figure 10. Maximum likelihood classification of ASTER image from 4/22/2006. Red areas are classified as buffelgrass. Red triangles represent ground reference points where buffelgrass was found and a black X represents reference points where buffelgrass was not found.

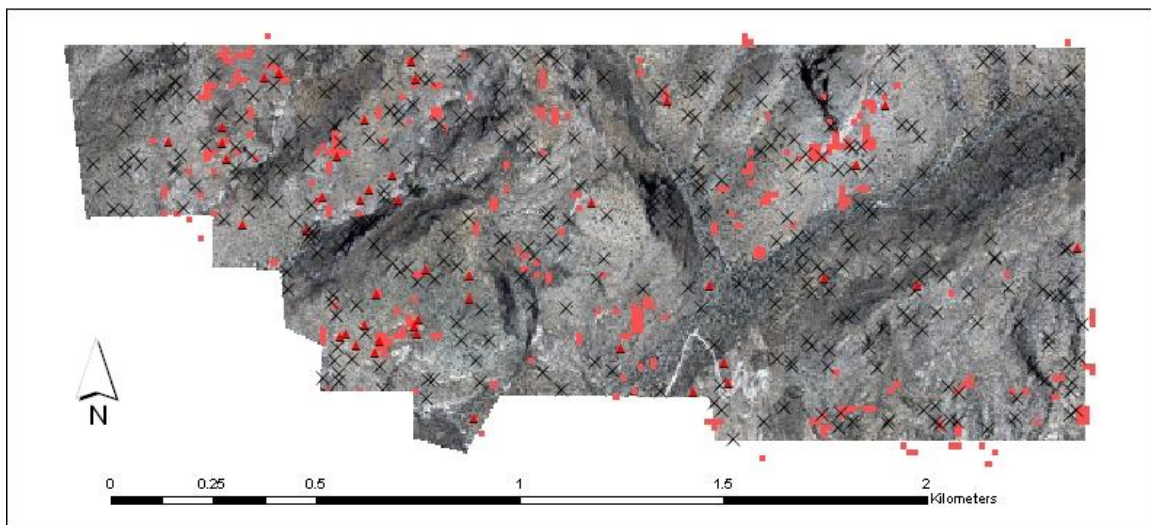


Figure 11. Maximum likelihood classification of ASTER image from 4/22/2006 with topography. Red areas are classified as buffelgrass. Red triangles represent ground reference points where buffelgrass was found and a black X represents reference points where buffelgrass was not found.

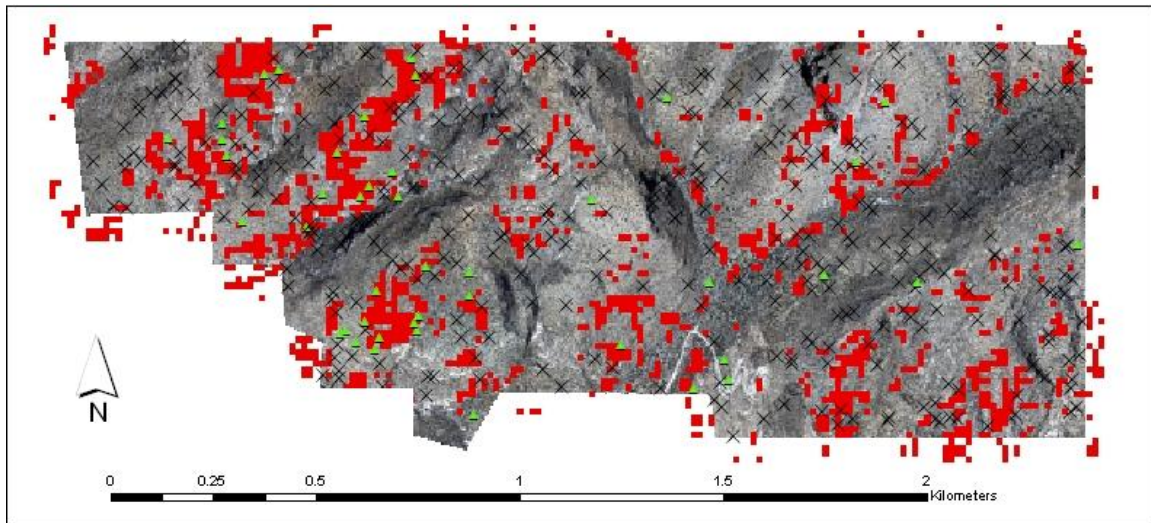


Figure 12. Maximum likelihood classification of ASTER image from 7/18/2006. Red areas are classified as buffelgrass. Green triangles represent ground reference points where buffelgrass was found and a black X represents reference points where buffelgrass was not found.

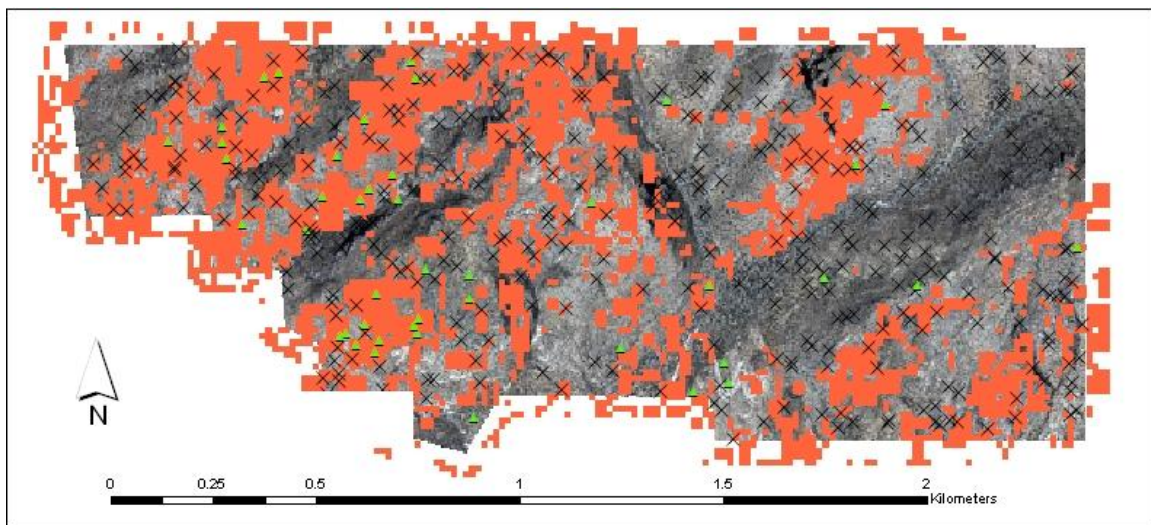


Figure 13. Maximum likelihood classification of ASTER image from 7/18/2006 with topography. Red areas are classified as buffelgrass. Green triangles represent ground reference points where buffelgrass was found and a black X represents reference points where buffelgrass was not found.

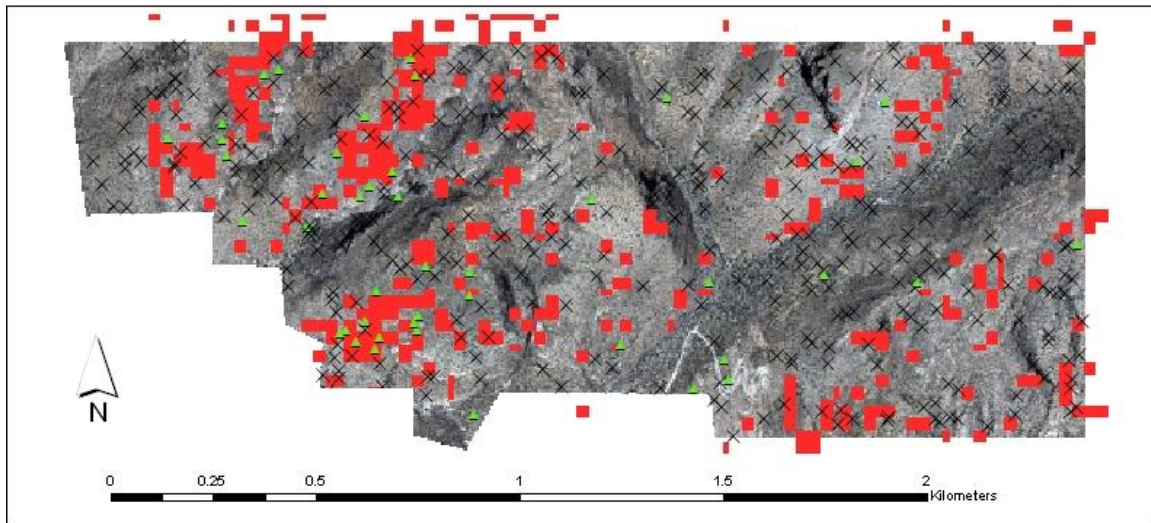


Figure 14. Maximum likelihood classification of ASTER image from 11/27/2006. Red areas are classified as buffelgrass. Green triangles represent ground reference points where buffelgrass was found and a black X represents reference points where buffelgrass was not found.

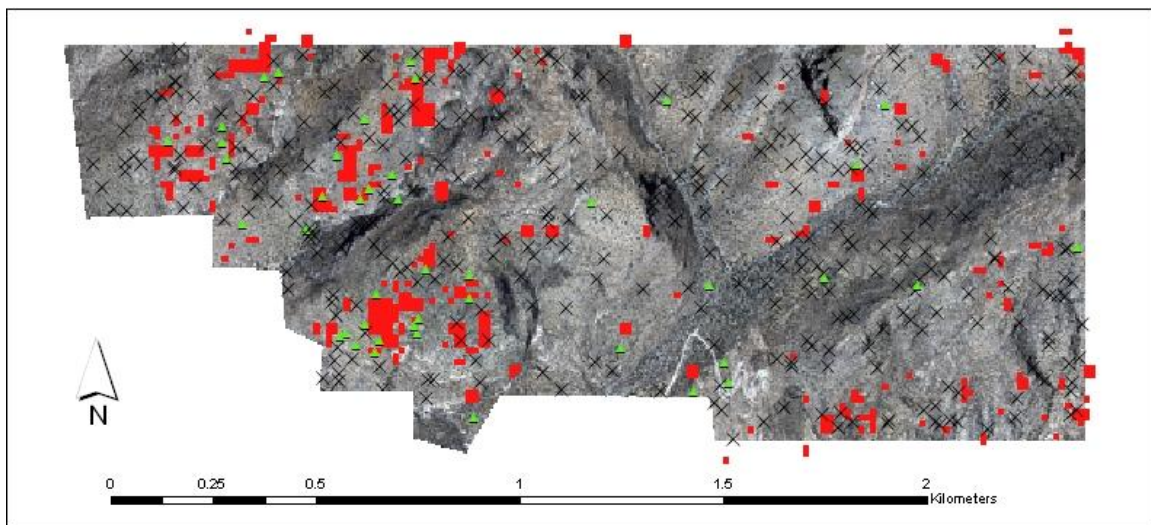


Figure 15. Maximum likelihood classification of ASTER image from 11/27/2006 with topography. Red areas are classified as buffelgrass. Green triangles represent ground reference points where buffelgrass was found and a black X represents reference points where buffelgrass was not found.

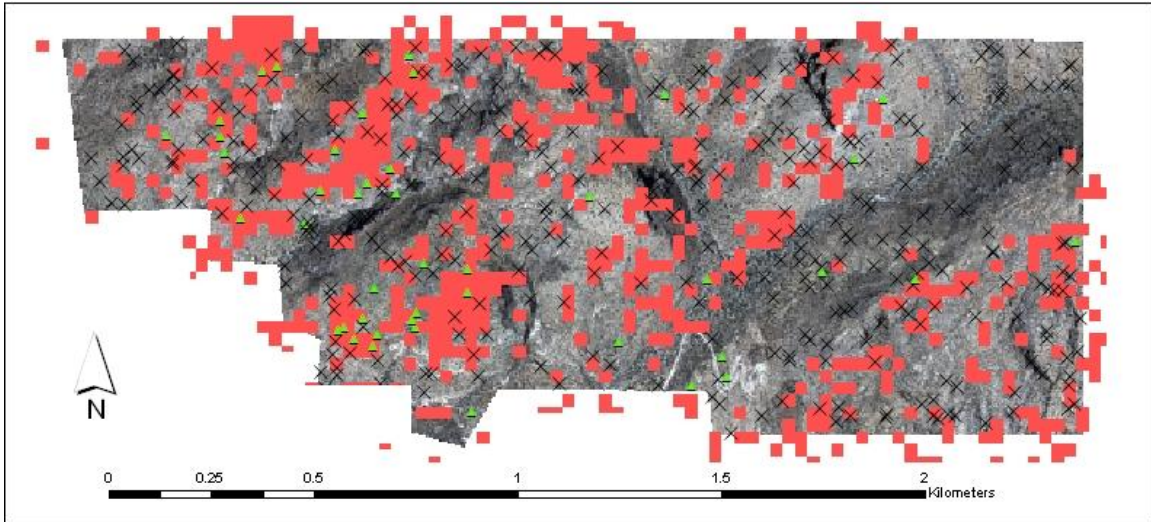


Figure 16. Maximum likelihood classification of Landsat TM image from 8/27/2006. Red areas are classified as buffelgrass. Green triangles represent ground reference points where buffelgrass was found and a black X represents reference points where buffelgrass was not found.

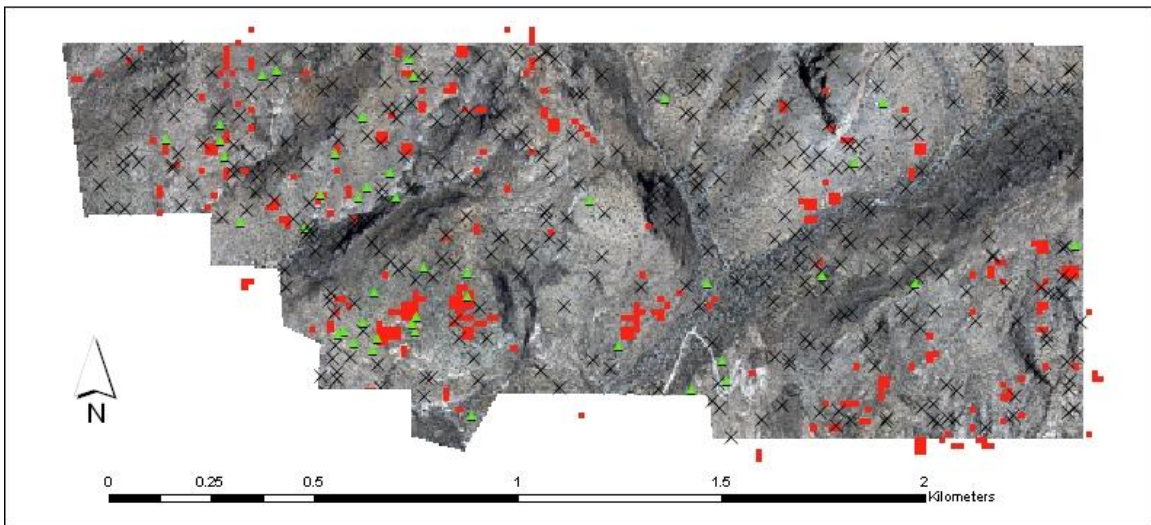


Figure 17. Maximum likelihood classification of Landsat TM image from 8/27/2006 with topography. Red areas are classified as buffelgrass. Green triangles represent ground reference points where buffelgrass was found and a black X represents reference points where buffelgrass was not found.

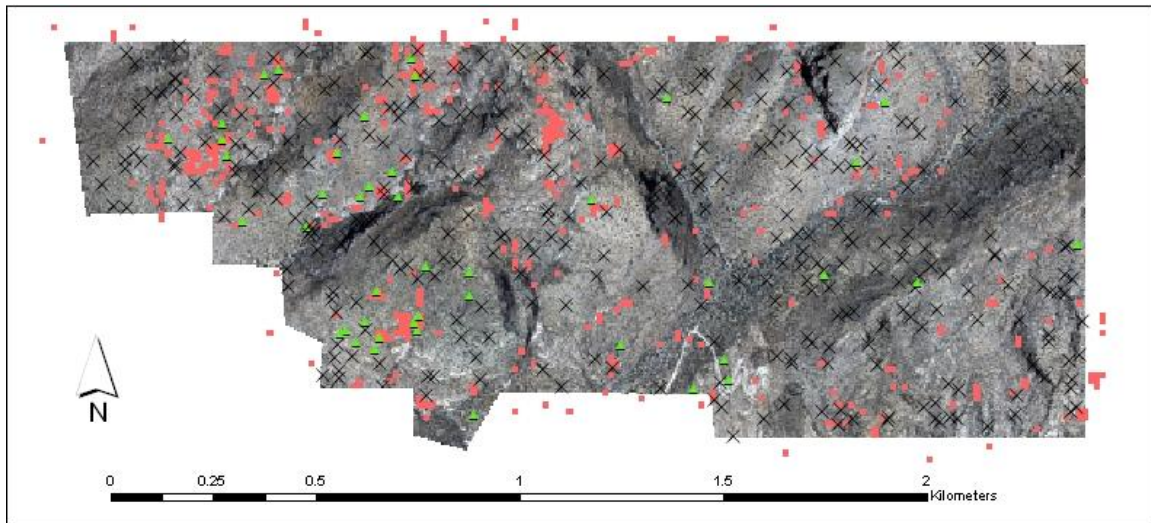


Figure 18. Maximum likelihood classification of ASTER scene composite from 4/22/2006 and 7/18/2006. Red areas are classified as buffelgrass. Green triangles represent ground reference points where buffelgrass was found and a black X represents reference points where buffelgrass was not found.

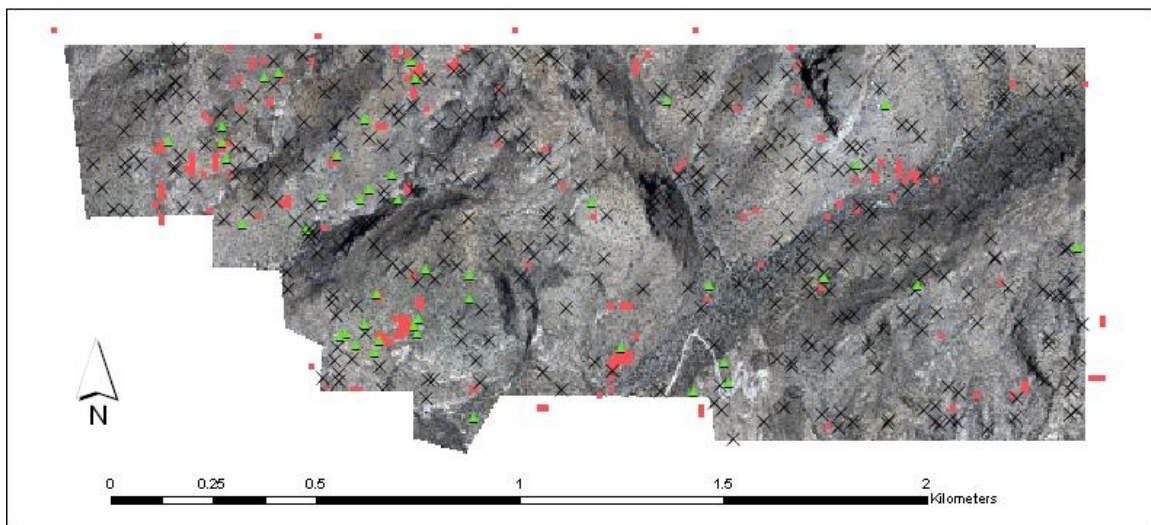


Figure 19. Maximum likelihood classification of ASTER scene composite from 4/22/2006 and 7/18/2006 with topography. Red areas are classified as buffelgrass. Green triangles represent ground reference points where buffelgrass was found and a black X represents reference points where buffelgrass was not found.

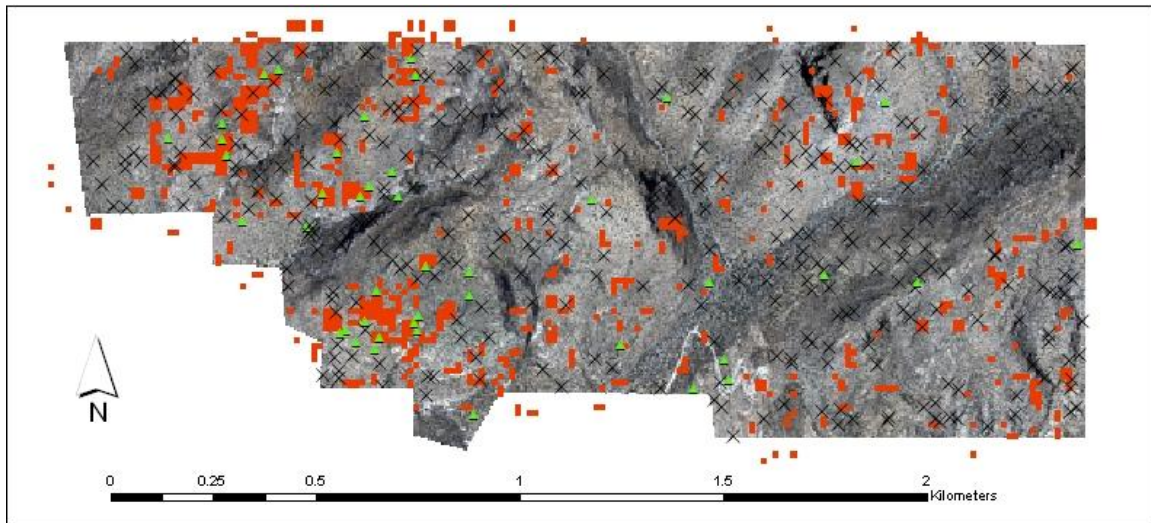


Figure 20. Maximum likelihood classification of ASTER scene composite from 7/18/2006 and 11/27/2008. Red areas are classified as buffelgrass. Green triangles represent ground reference points where buffelgrass was found and a black X represents reference points where buffelgrass was not found.

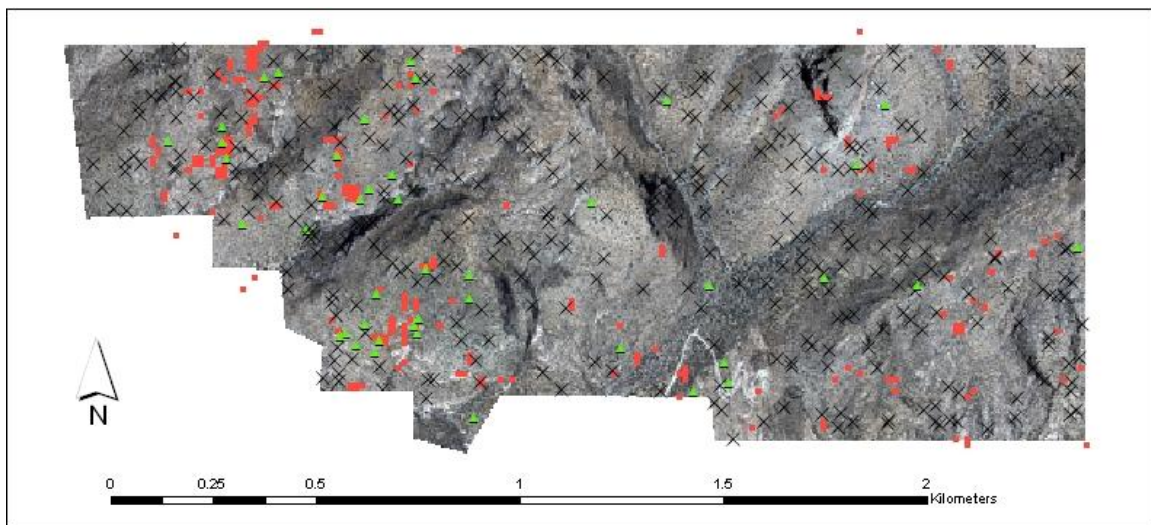


Figure 21. Maximum likelihood classification of ASTER scene composite from 7/18/2006 and 11/27/2008 with topography. Red areas are classified as buffelgrass. Green triangles represent ground reference points where buffelgrass was found and a black X represents reference points where buffelgrass was not found.

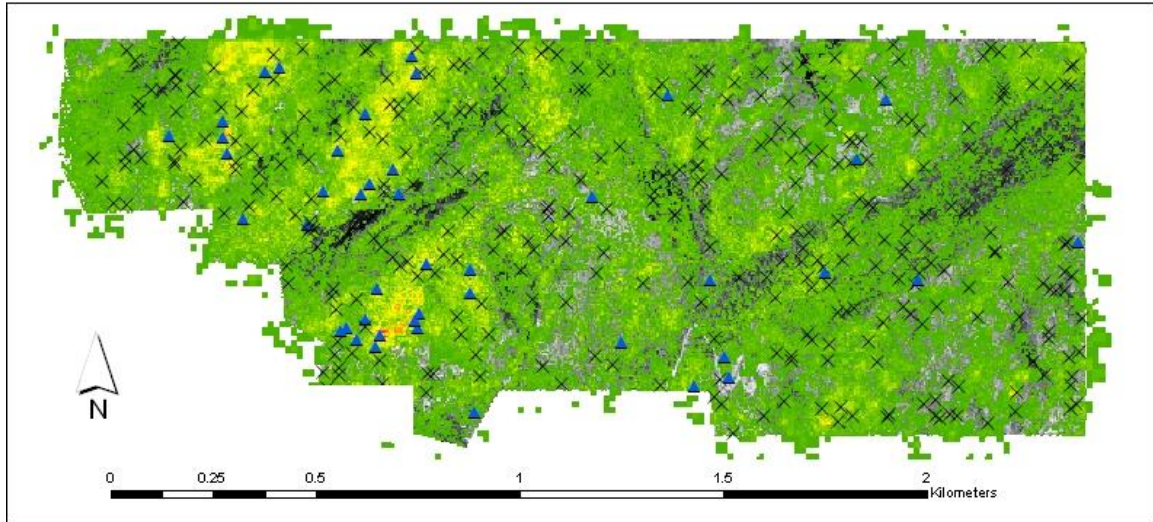


Figure 22. Binary ensemble model of buffelgrass as predicted from 20 maximum likelihood classifications. In the image, red colors correspond to areas predicted as buffelgrass by 10 or more models, while yellow corresponds with areas predicted by 5 or more models. Green corresponds to areas predicted as buffelgrass by at least one model. The blue triangles represent validation points where buffelgrass was present at the time of field work and the X's represent areas where buffelgrass was absent.

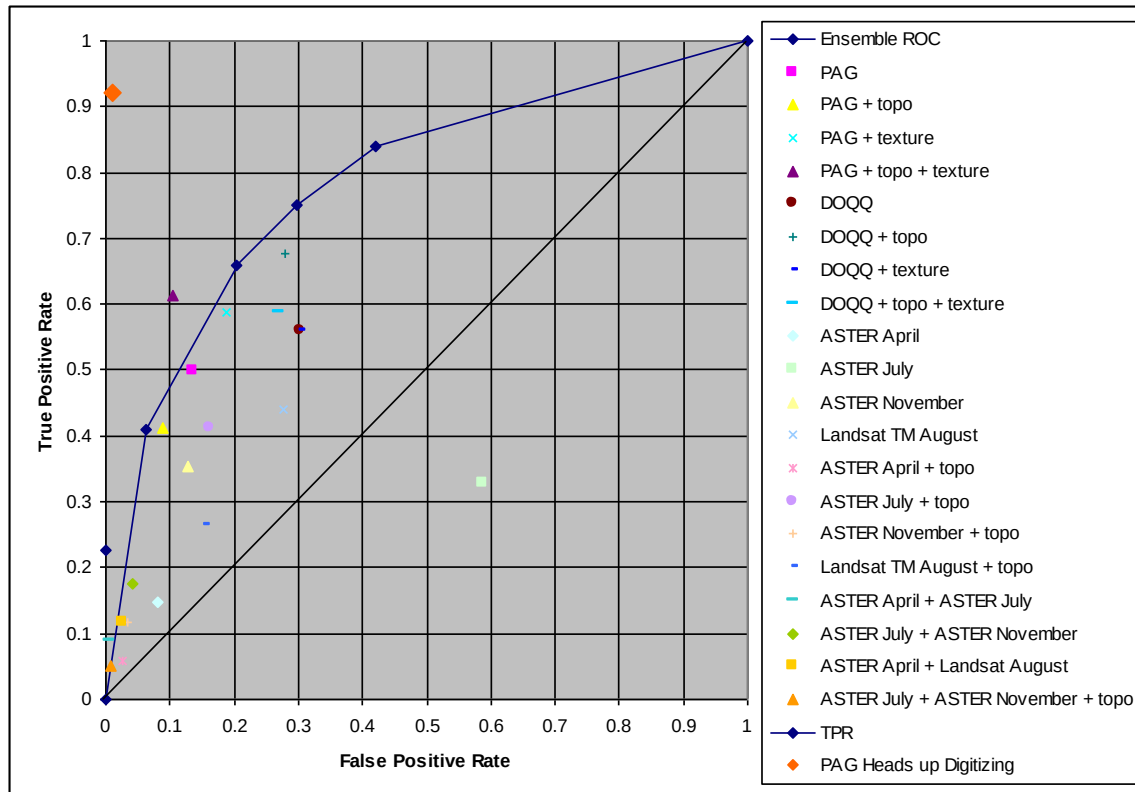


Figure 23. Receiver Operator Characteristic (ROC) Curve with scatter plots of individual classification results on the ROC plot.. In the ROC curve, models near the upper left (with a False Positive Rate of 0 and a True Positive Rate of 1) are most discriminating. Anything below the 1:1 line (shown as a diagonal line from lower left to upper right) is less discriminating than random assignment into groups. The PAG Heads up digitizing was the most discriminating, followed by the PAG + topo + texture. The area under the ROC curve is 0.78. The only models displaying more discrimination, as evidenced by plotting to the left of the ROC curve are the PAG + topo + texture and two multi-scene classifications. The low false positive rate for the two multi-scene classifications is indicative of models that predicted very few buffelgrass pixels in the classification. Not shown: Three-scene composite classifications, which did not correctly predict any buffelgrass reference points.

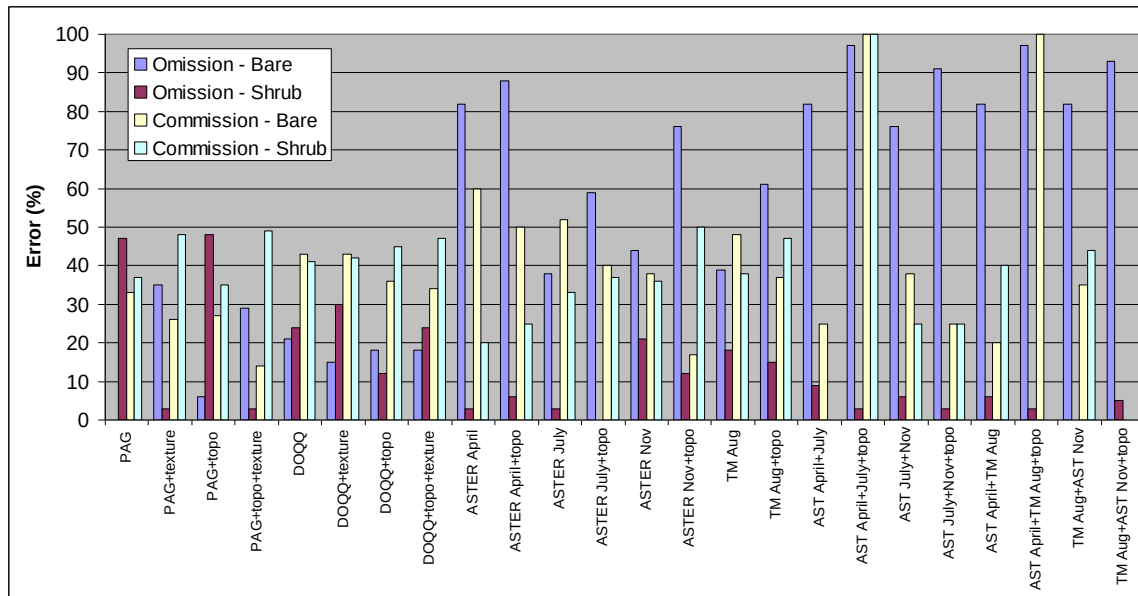


Figure 24. Summary of classification confusion for image datasets included in this study. The y-axis represents omission and commission errors. The datasets are listed along the x-axis. Each dataset is represented by 4 data points: Omission – Bare (the percentage of buffelgrass reference points classified as either rock or soil), Omission – Shrub (the percentage of buffelgrass reference points classified as either shrub or tree), Commission – Bare (the percentage of rock or soil reference points classified as buffelgrass), and Commission – Shrub (the percentage of rock or soil reference points classified as buffelgrass).

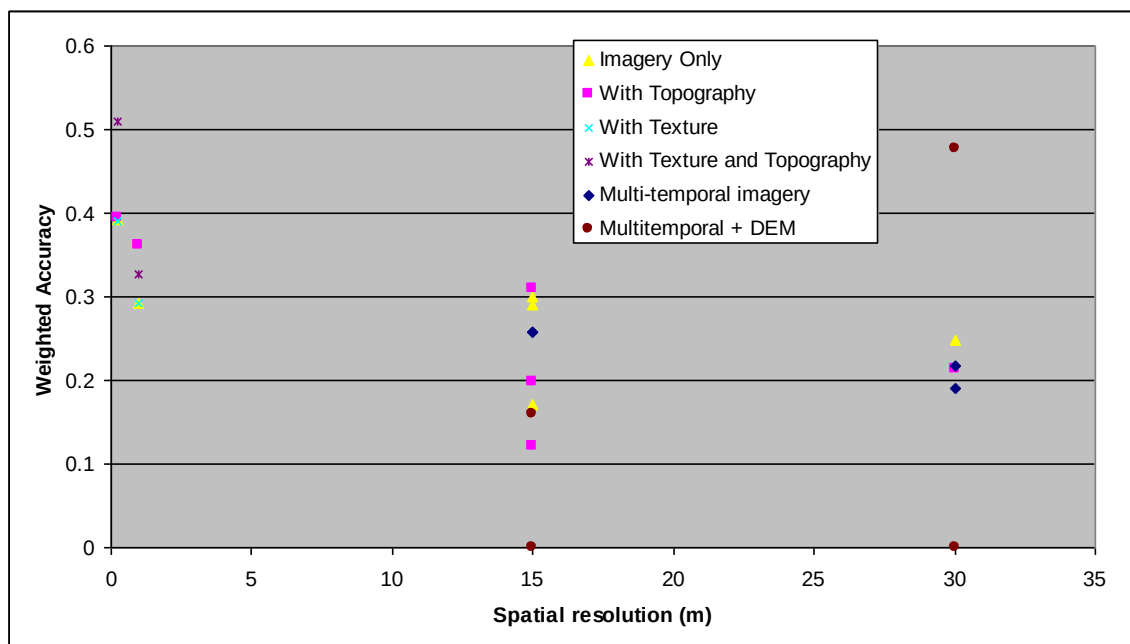


Figure 25. Weighted accuracy of classifications with respect to spatial resolution. Weighted accuracy is the geometric mean of the producer's and user's accuracy.

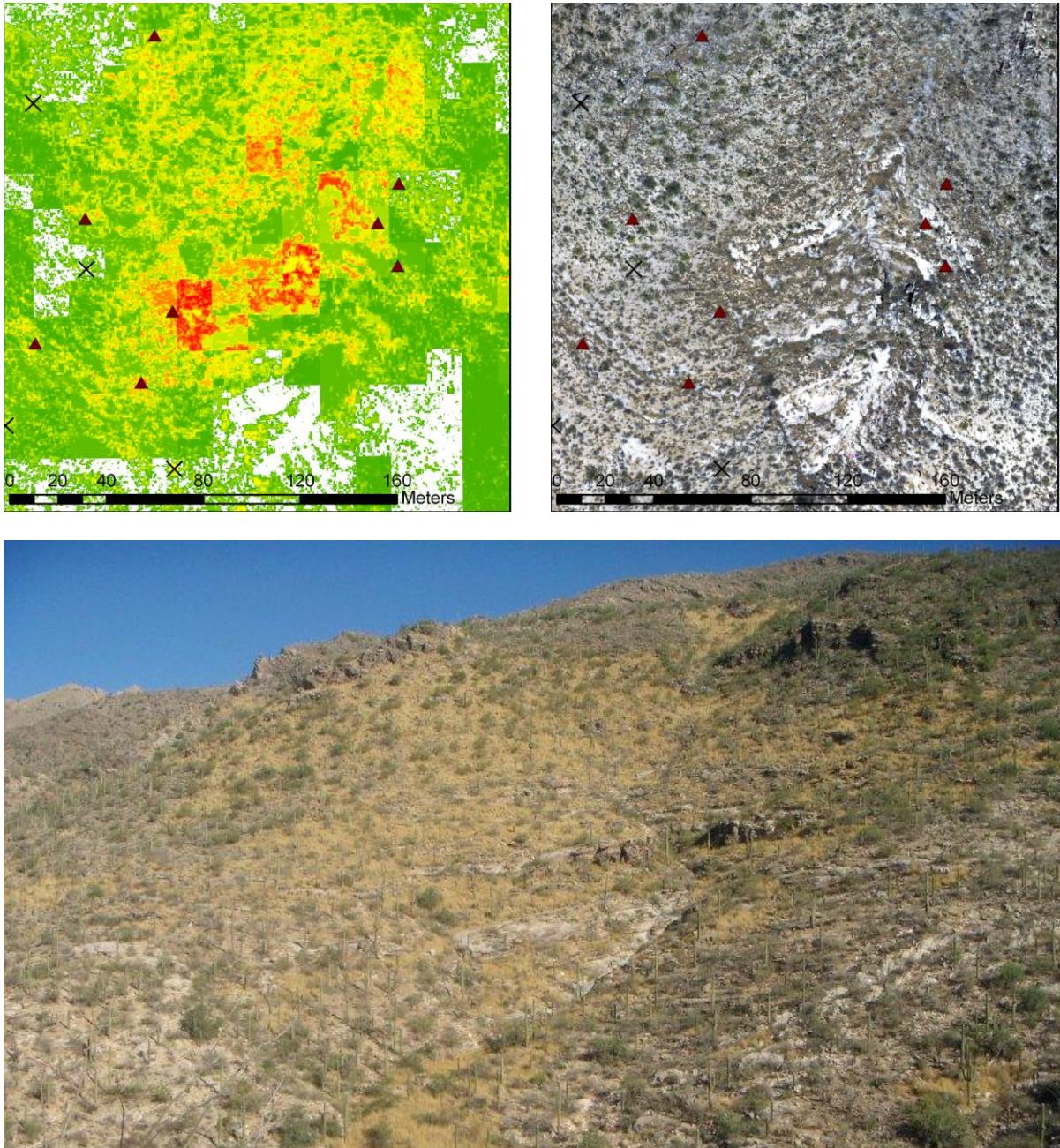


Figure 26. Closeup of the most heavily infested area of buffelgrass in the study area. Upper left: Ensemble classification of buffelgrass. This patch was consistently classified by the models as buffelgrass, as evidenced by the red colors. Validation points showing buffelgrass presence are shown as dark red triangles, whereas validation of buffelgrass absence is shown as black X's. Upper right: PAG 0.33-m aerial photograph of same area. Bottom: Photograph of patch, facing north-northwest. Buffelgrass is clearly visible in yellow. Also visible are saguaros (*C. gigantea*), shrubs (mostly *P. microphylla*), rock outcrops, and bare soil.

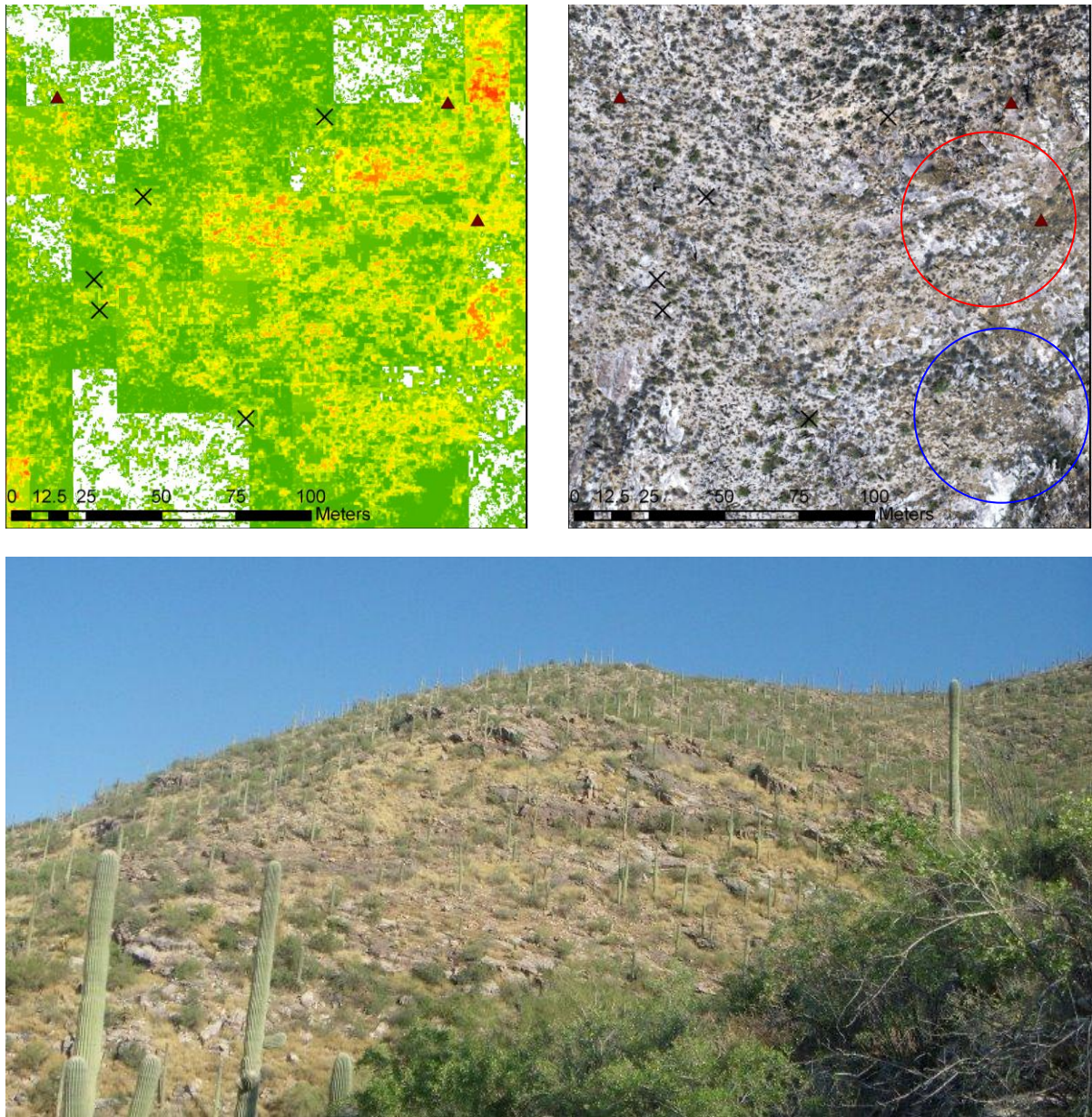


Figure 27. Closeup of heavily infested slope of buffelgrass. Upper left: Ensemble model of buffelgrass, with the most frequently predicted areas in red and the least frequently predicted areas in yellow. Validation points are given as red triangles (buffelgrass) and X's (absence). Upper right: PAG aerial photograph. The area circled by red was consistently classified as buffelgrass, but the area circled in blue was only classified by a minority of models. Bottom: Photography taken from below the patch, looking north-northwest. Buffelgrass is clear in this photo as a yellow hue, while rock, bare soil, shrubs, and saguaros are also visible.

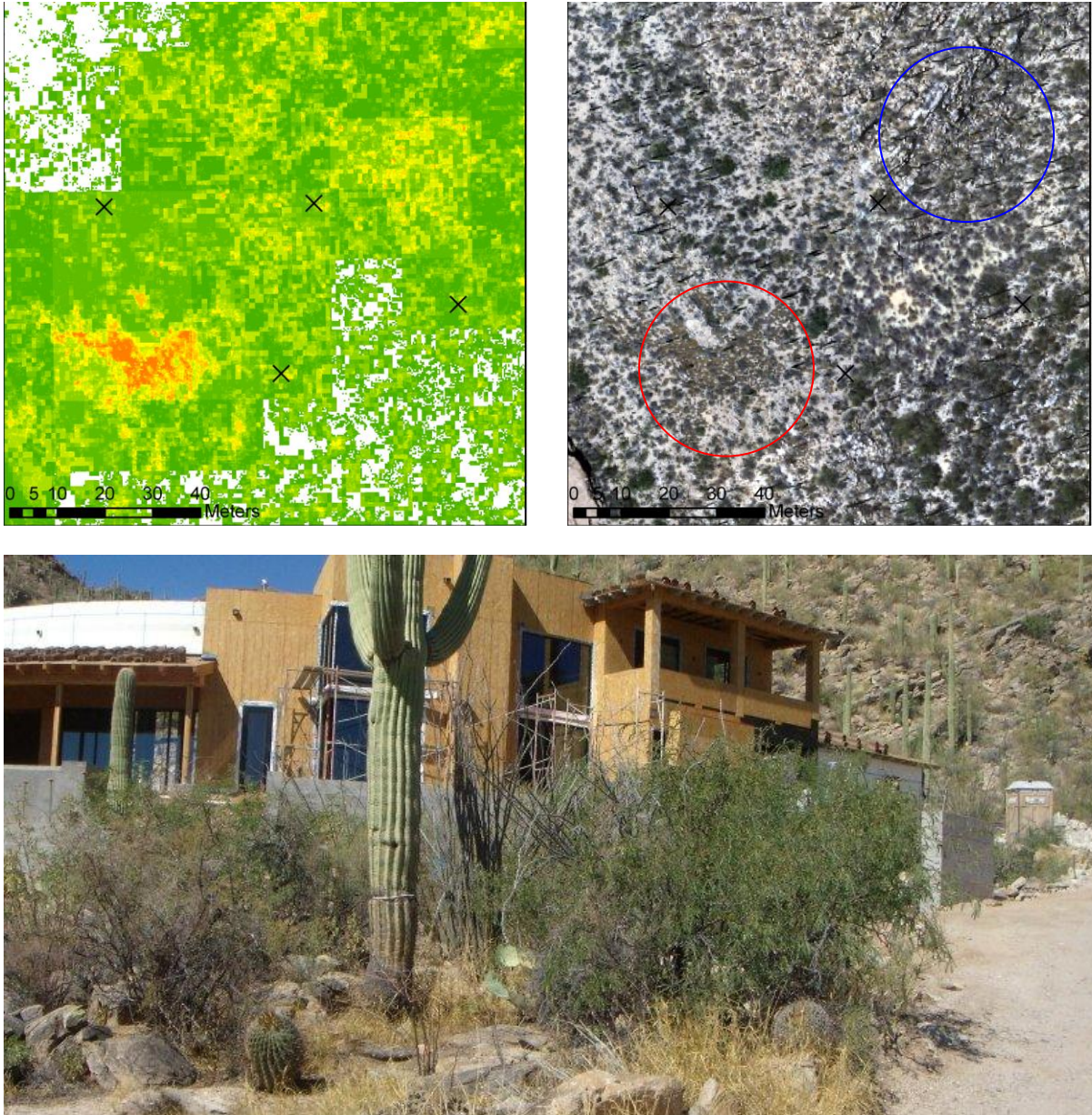


Figure 28. Closeup of an area with one large patch of buffelgrass and several smaller infestations. Upper left: Ensemble model with high probability of buffelgrass (red), medium probability (yellow), and low (green). Validation points are given as red triangles (buffelgrass) and X's (absence).. Upper right: Aerial photograph of same area. Bottom: photo of area taken in 2008, after development occurred directly in the middle of the patch. The large infestation shown encircled in red was classified correctly by most of the classifiers. Although there are smaller patches within this area, the large patch was handled quite well. However, perennial shrubs on this slope were also classified as buffelgrass (blue circle, upper left).

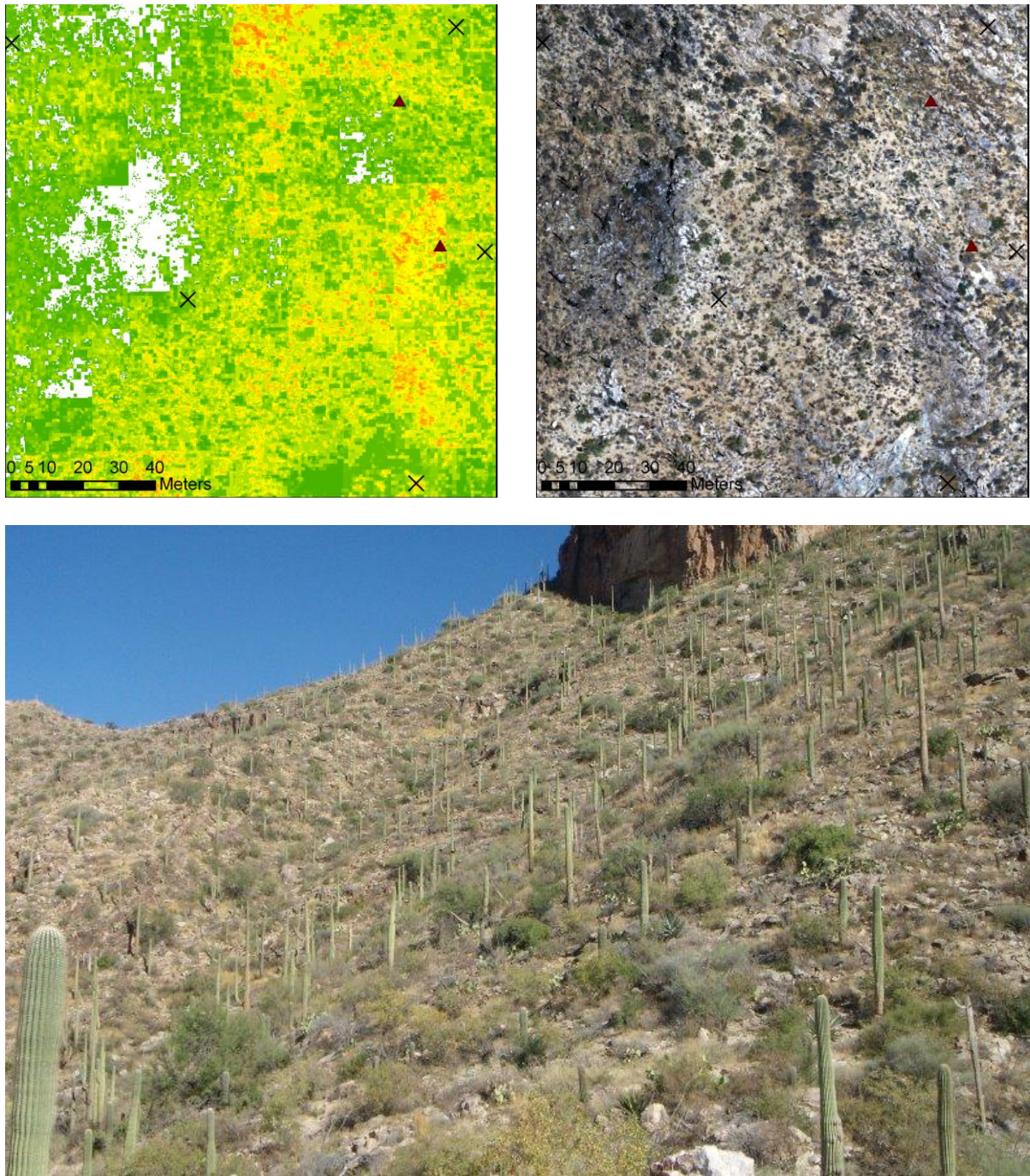


Figure 29. Closeup of buffelgrass-free area with reddish soil. Upper left: ensemble model prediction with areas of high probability (red), medium (yellow), and low (green). Validation points are given as red triangles (buffelgrass) and X's (absence). Use of texture did not increase the separability of these two classes. Upper right: aerial photograph of same area. Bottom: photograph of same area taken from bottom right of map looking north-northwest. This area was consistently classified by buffelgrass when the PAG imagery and DOQQs were used because the hue is similar to that of buffelgrass

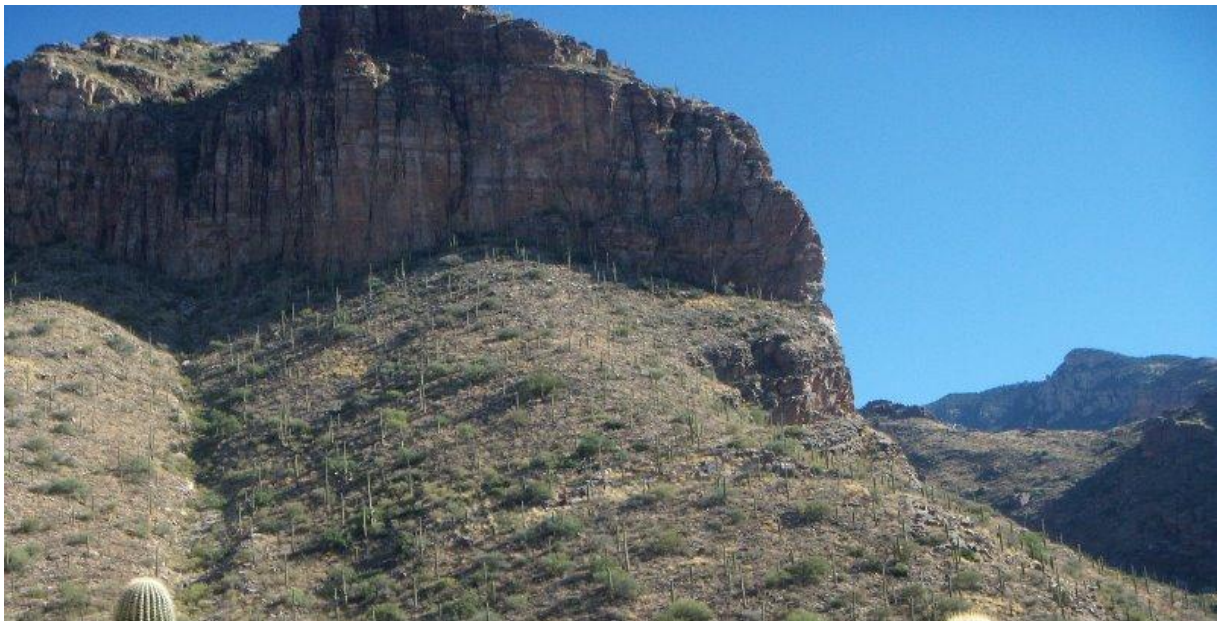
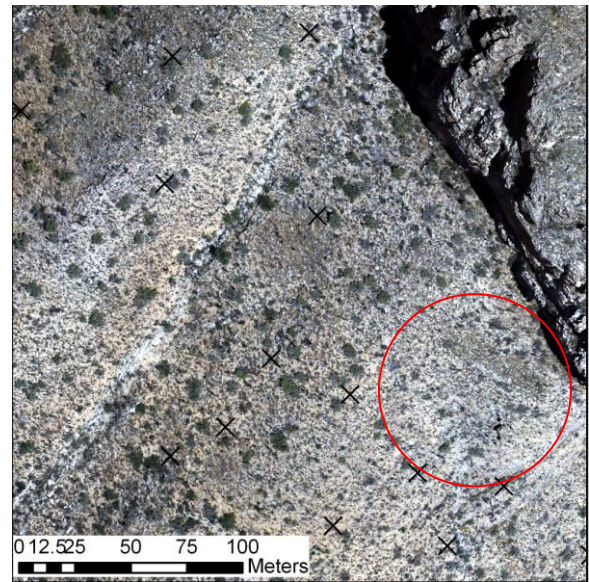
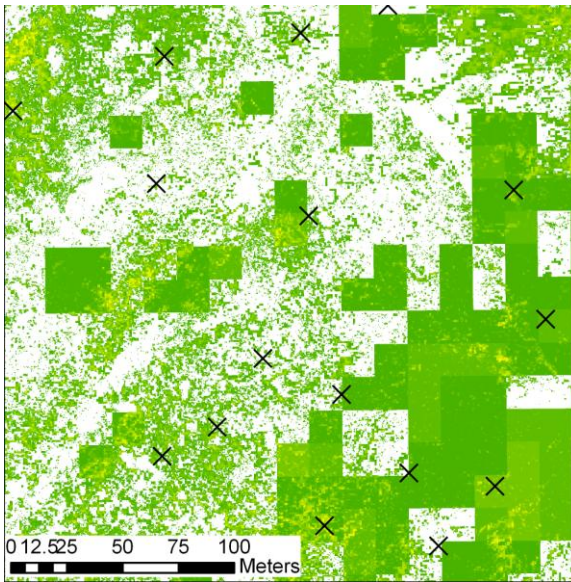


Figure 30. Closeup of Satellite infestations on hillslope. This slope has a number of buffelgrass patches growing from the base of the cliff shown at the far right. The largest one, visible as a fuzzy brown spot inside the red circle, was not classified by most of the classifiers. The reddish soil on the far left of the screen was classified more often as buffelgrass, even when texture and topography was included. Validation points are given as red triangles (buffelgrass) and X's (absence)



Availability of PAG Imagery for Saguaro National Park, Rincon Mountain District

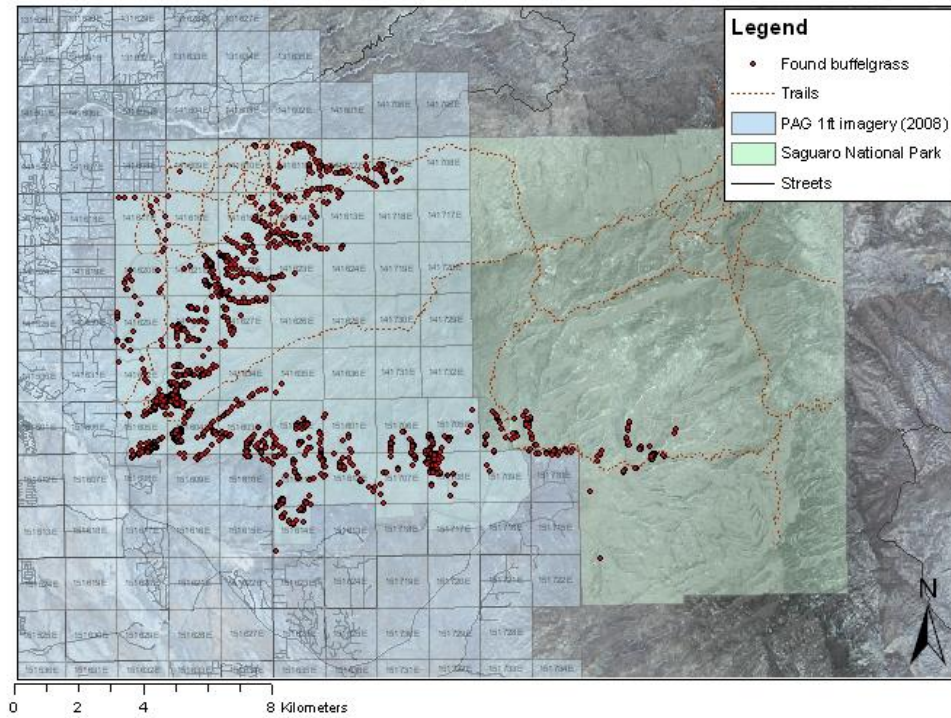


Figure 31. Availability of 0.31m PAG imagery from 2008 for Saguaro National Park, Rincon Mountain District. PAG imagery, available in PLSS sections, are shown in blue overlying approximately 35% of the Rincon Mountain District and 80% of known buffelgrass locations (shown on the map in red). Future PAG imagery acquisitions could be expanded to include areas not imaged in 2008.

Availability of PAG Imagery for Saguaro National Park, Tucson Mountain District

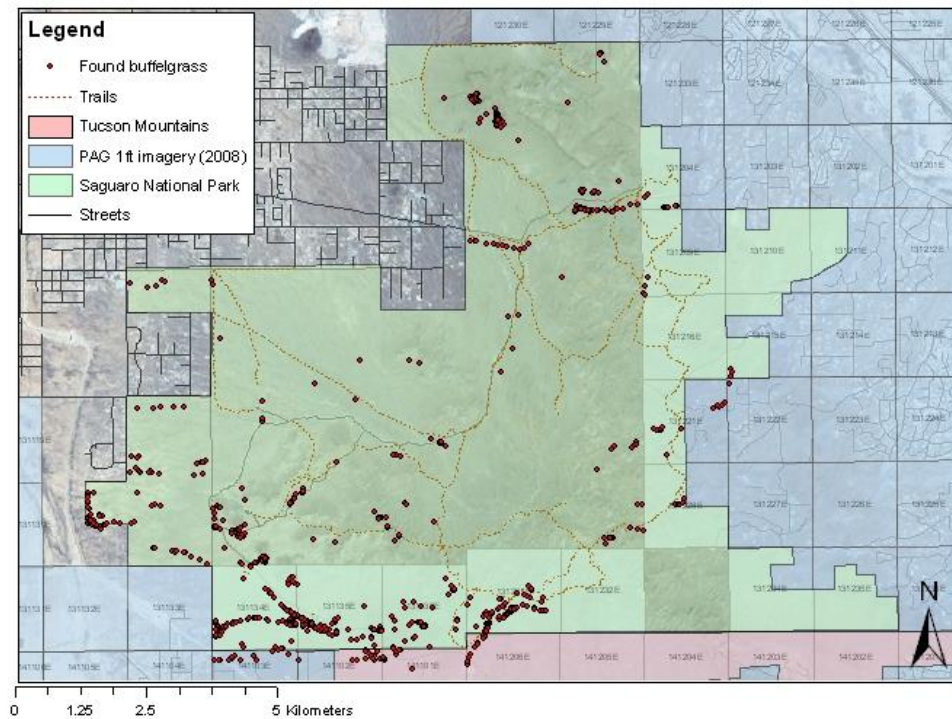


Figure 32. Available 0.31m PAG imagery from 2008 for Saguaro National Park's Tucson Mountain District. PAG imagery, available in PLSS sections, are shown in blue overlying approximately 10% of the Rincon Mountain District and 20% of known buffelgrass locations (shown on the map in red). Saguaro National Park could partner with PAG for future image acquisitions to ensure that the entire district is imaged.