# Detecting war-induced abandoned agricultural land in northeast Bosnia using multispectral, multitemporal Landsat TM imagery

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# Abstract

The use of satellite technology by military planners has a relatively long history as a *tool* of warfare, but little research has used satellite technology to study the *effects* of war. This research addresses this gap by applying satellite remote sensing imagery to study the effects of war on land-use/land-cover change in northeast Bosnia. Though the most severe war impacts are visible at local scales (e.g. destroyed buildings), this study focuses on impacts to agricultural land. Four change detection methods were evaluated for their effectiveness in detecting abandoned agricultural land using Landsat Thematic Mapper (TM) data from before, during, and after the 1992-95 war. Ground reference data were collected in May of 2006 at survey sites selected using a stratified random sampling approach based on the derived map of abandoned agricultural land. Fine resolution Quickbird imagery was also used to verify the accuracy of the classification. Results from these analyses show that a supervised classification of the Landsat TM data identified abandoned agricultural land with an overall accuracy of 82.5%. The careful use of freely available Quickbird imagery, both as training data for the supervised classifier and as supplementary ground reference data, suggest these methods are applicable to other civil wars too dangerous for researchers' field work.

## 1. Introduction

The development and use of satellite imagery and aerial reconnaissance have long been tied to improving the effectiveness of military operations. From photoreconnaissance using lighter than air balloons to aircraft platforms and finally satellite remote sensing, battlefield remote sensing has been a key imaging application (Corson and Palka 2004). Non-military use of such imagery are more limited. Though some wartime scars such as bullet-pocked walls and abandoned buildings are difficult to detect from an aerial viewpoint, other war impacts such as the mass displacement of local residents can lead to land-cover changes such as the abandonment of agricultural land that are more readily detectible.

While remote sensing technology has been driven by these military applications, most academic researchers have devoted their efforts to land cover and land use applications with little attention to the effects of military action (de Sherbinin et al. 2002). But in a recent report from the US Climate Change Science Program (2003, p66), the Subcommittee on Global Change Research identified as a key question for future research the study of 'How, and to what extent, do extreme events (e.g. natural hazards, public health emergencies, and *war*) affect land-use and land-cover change'? (my italics) The extent of war impacts that can be detected is a function of the cross-sectional imprint from space on the land and the resolution of the satellite sensor. So while individual mines cannot be detected by commercial remote sensing platforms, their effects on land cover can be detected when re-vegetation in agricultural areas occurs or new service roads are constructed (Maathuis 2003).

The objective of this study is to compare four change detection methods in order to understand better the effects of war on land-use/land-cover change in Bosnia-Herzegovina (BiH). The study uses multispectral, multitemporal Landsat data to measure abandoned agricultural land in northeast Bosnia. Since abandoned agricultural land lacks the cyclical plowing, sowing, and harvesting of active fields, the satellite imagery were selected to detect these key differences in vegetation over time. Multiple change detection algorithms were evaluated before selecting one most appropriate for the set of acquired satellite images.

## 2. Background

The war in BiH was a struggle between the three main ethnicities, Serbs, Bosniaks (Muslim Bosnians), and Croats over how the territory of Bosnia-Herzegovina should be demarcated. Serbs in what remained of Yugoslavia largely supported the effort to control BiH as part of a 'Greater Serbia' in the remnants of Yugoslavia after Slovenia and Croatia left in 1991. Bosniaks and Croats, influenced by the recently independent Croatia, supported an independent BiH, separate from Yugoslavia. This led to a three year war from March 1992 to November 1995 that cost over 100 000 lives and displaced some two million residents from their homes (Ó Tuathail and Dahlman 2004, Tabeau and Bijak 2005).

### 2.1. *Impacts to the landscape from the BiH civil war*

In addition to the severe human toll, the effects of the war are also still clearly visible in the physical landscape and economy of BiH. Transportation infrastructure suffered damage or destruction to 35% of the main roads and 40% of the bridges. The combined effects of industrial infrastructure destruction and rampant inflation led to a near collapse of industrial production with output dropping 80% by 1993, followed by only a modest recovery after the war (UNECE Committee on Environmental Policy 2004).

Agricultural productivity faced similar declines. Of BiH's 5.1 million hectares of land, 50.3% is agricultural, with less than 20% of this land suited to intensive agriculture due to high altitude, steep slopes, and poor soil fertility (Custovic 2005). During the war, most of the irrigation systems (serving 10 000 ha) were heavily damaged or destroyed (Custovic et al. 2004). Also, 70% of tractors and other agricultural tools were destroyed and 60% of livestock disappeared during the war. In all, the pre-war (1988-91) average cultivated area decreased by 25% when compared to the post-war (1996-2004) average cultivated area (H. Custovic, personal communication, 15 August 2005).

In addition to destroyed equipment and transportation infrastructure, the widespread placement of landmines also inhibited cultivation of land and has continued to deter residents from returning (Bolton 2003). Interviews conducted during May of 2006 with the Director of the Agrokoperative in Bratunac BiH, Marko Blagojević, and the Brčko BiH Agricultural Minister, Krsta Jesinic, confirmed that war-time landmines caused some of this decline in productivity, but that markets and contracts lost during the war have since been filled by competitors from other countries, presenting a further obstacle to agricultural recovery.

Concerns about landmines are still quite high since 200 000 ha of agricultural land are mined and de-mining efforts are expected to last 40 years (REC 2000). Though the Bosnia-Herzegovina Mine Action Centre (BHMAC) together with international aid organisations have invested considerable effort to mitigate the risks posed by landmines, dozens of people are killed or injured by landmines and unexploded ordnance in BiH each year and over 2000 km$^2$ of land (4.09% of all land) is still contaminated by up to one million landmines and unexploded ordnance (Mitchell 2004, BHMAC 2006). In areas that experienced heavy fighting such as Brčko (part of the study area), the proportion of mined land is as high as 13%.

From the perspective of satellite imagery, abandoned cropland shows an increase in vegetation vigor since fields are not annually plowed or harvested. Using satellite imagery, there has been some effort to identify abandoned agricultural land in the former Yugoslavia by the International Trust Fund for Demining (ITF 2002) and the Food and Agricultural Organization of the UN (FAO CTA and Biancalani 2002), but the results from these studies are poorly documented with respect to methodological details and accuracy assessments.

### *2.2. **The remote sensing of war impacts***

Academic research linking remote sensing data and war is limited, though growing. Satellite reconnaissance became available after 1960 and played the significant role of providing information concerning enemy missiles, planes, and tanks during the Cold War and subsequent major military engagements (Corson and Palka 2004). Such military uses of remote sensing technology are driven by strategic battlefield goals, with little concern for any broader war impacts (Singh 2000).

Studies that consider the social and environmental effects of war using satellite imagery can be grouped into two categories: i) those that focus on the *direct* impacts of war resulting from bomb detonations, military movements, and minefields and ii) those that consider the *indirect* impacts of war that result from displaced persons and their environmental imprint.

For the first category, *direct* impacts, most of the non-military satellite analysis has focused on the 1991 Gulf War, with limited attention to other conflicts. The environmental consequences of the first Gulf War were extensively studied using primarily moderate and coarse resolution satellite imagery, spurred by the massive environmental impacts resulting from military vehicle movements, hundreds of oil well fires, and numerous oil lakes (Williams et al. 1991, El-Baz and Makharita 1994, Husain 1994, Koch and El-Baz 1998, Kwarteng 1998, Abuelgasim et al. 1999). Recent military activity in Iraq, in particular the oil trench fires around Baghdad in March of 2003, have prompted further satellite monitoring using Landsat and IKONOS imagery (UNEP 2003a). Other remote sensing applications to conflict areas focus on urban impacts. For these applications, finer resolution imagery from the IRS (6 m), IKONOS (1 m), and Quickbird (60 cm) platforms are most effective in detecting bomb detonations, destroyed buildings, and razed villages (UNEP and UNCHS 1999, Al-Khudhairy et al. 2005, Lempinen 2006). The arid and semi-arid climate of Iraq and Kuwait means that few of the methods used in these studies are directly transferable to the humid subtropical climate of northeast Bosnia.

In the second category of war impacts (*indirect*), displaced persons often have the largest impact on the environment. Refugee camps created to take in those fleeing unstable areas place significant stress on the surrounding land and water resources. Fine resolution remote sensing imagery has been increasingly used to monitor the spatial extent of these camps with an eye towards more efficient management as well as to assess the impact on surrounding forests (Lodhi et al. 1998, Bjorgo 2000, UN General Assembly Economic and Social Council 2000, Giada et al. 2003, Bally et al. 2005). A few studies document the effect that conflicts can have on deforestation (UNEP 2003b) and reduced agricultural productivity (Howes 1979, Smith 1998).

Though the UN is the leader in the use of satellite data to assist in humanitarian efforts, very little academic research has used the imagery to analyse the effects of war from such a synoptic view. One impediment to such work is the risk in war and post-war zones to the researcher in carrying out the requisite field work. In BiH, where no fighting has occurred in over a decade, the predominant risk is from unexploded ordnance and landmines. Elsewhere, post-war assessments can be nearly impossible as in the cases of El Salvador, Vietnam, and the first Gulf War where researchers were threatened or even killed, and data and equipment destroyed or confiscated (Brauer 2000). Given the increased availability of mid to fine resolution (better than 36 m pixels) satellite imagery since the early 1990s (Stoney 2006) and the increase of civil wars over the same period (Sarkees et al. 2003), this research field holds much potential for assessing the burden of war by identifying impacts with a view to aid the victims.

### *2.3* ***The remote sensing of abandoned agricultural land***

Since changes in agricultural land use represent the largest impact to the landscape from the war in BiH, this section considers the remote sensing requirements for studying agriculture land-use change. For agricultural studies, detailed knowledge of crop phenology and spectral properties are required in addition to multiple satellite images for each growing season to measure these life cycle changes (Bauer 1985, Jensen 2000, Rundquist et al. 2002). Multiple satellite images allow for the detection of trends in vegetation density such as consistent increases over many years associated with abandoned fields or cyclical densities where bare soil is exposed after the land is plowed. The spectral and radiometric resolutions must be sufficient to identify these changes, typically visible in the red and near infrared spectrums.

Also key to identifying abandoned agricultural land are the temporal and spatial resolution of the data required to detect the changes. Peterson and Aunap (1998) found that Landsat MSS data over a time period of 3 years was insufficient for detecting abandoned state farms in Estonia. For decadal time periods and very large study areas, however, coarse 8 km resolution AVHRR data were able to detect increases in vegetation due to the collapse of the Soviet Union (de Beurs and Henebry 2004). Longer time periods of 10-15 years are also effective in detecting abandoned agricultural land using moderate resolution Landsat TM and MSS data in Spain and the Upper Midwest, USA (Brown 2003, Romero-Calcerrada and Perry 2004).

For war-induced agricultural land-use changes, Landsat, IRS, and SPOT imagery of Kosovo over a short two year time period were evaluated using a visual photo interpretation method, but the results for fallow land use were undermined by large error values (Terres et al. 1999). Better results for detecting abandoned agricultural land were achieved using supervised classifications in Croatia over a nine year time period with fine resolution KVR imagery, aerial photographs, and a small (12 km$^2$) study area (Landsberg et al. 2006).

Overall, most of the agricultural land abandonment studies use a post-classification change approach, but applying such an approach in BiH is difficult. To classify the pre-war imagery, accurate ground reference data to train the classifier are necessary. These data are difficult to obtain for BiH given the historical nature of the imagery which limits the availability of high resolution aerial photographs and satellite imagery. Therefore, this study does not attempt to create a comprehensive land cover classification and instead focuses on identifying areas of abandoned agricultural land based on the changes in the spectral signatures.

## *3. Data*

### *3.1* ***Study area***

The study area comprises 48 *opstini* (similar to counties) in northeast Bosnia (Figure 1) covering 13 887 km$^2$. This sub-region of BiH was chosen for several reasons. The region was the focus of intense fighting and ethnic cleansing and therefore contains a considerable number of minefields, especially along the Inter-Entity Boundary Line (IEBL) which was also the line of confrontation between the respective armies during the war. Also, the land use of this area is predominantly agricultural, though forest land dominates away from the riparian border (rivers Sava and Drina) with Croatia and Serbia. Lastly, the region was selected to include land on both sides of the IEBL to allow for any political effects and to include un-mined areas away from the IEBL. In this way, the study area includes areas heavily and lightly affected by the war.

The climate of the study area is subtropical humid with average temperatures ranging from about 1°C in January to 21°C in July. Average annual precipitation for this region of BiH is 800mm. Physiographically, the northern portion of the study area from Bosanska Gradiška to Bijeljina is a flatland area with elevations 80-300m above sea level. Towards the south and east from Doboj to Srebrenica, the terrain is much hillier and higher, 300-700m above sea level (Custovic 2005).

In terms of agricultural activity, the continental crop calendar for BiH (Table 1) shows that most summer crops such as corn are sown in April and May (some in March) and harvested in August and September. Winter crops tend to be sown in September and October and harvested the following June and July (H. Custovic, personal communication, 11 September 2005). Therefore, spring (April, May, June) and summer (July, August, September) satellite scenes were selected to ensure identification of plowed and harvested fields, whether sown with winter or summer crops.

### *3.2. **Satellite and land cover data***

Two Landsat scenes cover the agricultural regions in northeast Bosnia (Figure 1) and provide the requisite spatial, temporal, and spectral resolution. Individual Landsat scenes were selected based on the need to acquire a phenological record of the agricultural growing season from both before and after the war. In agricultural land use studies, vegetation phenology is especially important due to the sudden changes in reflectance associated with crop planting and harvesting (Bauer 1985; Jensen 2000; Rundquist et al. 2002). Scenes were acquired from before the war for the years 1990-1992 and the most recent years available, 2004 and 2005, to coincide most closely with the ground reference data.

Cloud-free scenes are often difficult to obtain over northeast Bosnia given the high amount of precipitation that falls in May and June (EuroWeather 2005). For path 188, row 29 (west scenes), no spring or summer scenes for 1992 were available. As an alternative, good quality pre-war scenes from 1990 and 1992 were selected (Table 2). The most recent scenes available for this path/row was in 2004, while path 187, row 29 (east scenes) had imagery available from 2005. Though most of the scenes have very little cloud cover, the clouds that are present tend to cluster over the mountainous regions of BiH south of the study area and were not a major hindrance in the analysis. Pixels contaminated by clouds or cloud shadows were masked and excluded from the analysis. The Landsat imagery were acquired from the University of Maryland's Earth Science Data Interface at the Global Land-Cover Facility, Yale University's Center for Earth Observation, USGS, and Eurimage.

Additional data used in the analysis were the Corine Land Cover (CLC) data obtained from the European Environment Agency for Bosnia-Herzegovina (EEA 2000). These data were derived from 1998 Landsat imagery and are available at 100 m pixel resolution. The accuracy of this dataset is quite good, with an overall classification reliability of 87 ± 0.8% (EEA 2006). Furthermore, the accuracy of well-defined categories such as arable land and coniferous forest is between 90 and 95%. This dataset was used to subset the analysis area to include only agricultural land (a category that includes recently abandoned agricultural land) since creating an exhaustive land cover classification was not feasible for the study area. The agricultural land category is composed of four main sub-categories: arable land (irrigated and non-irrigated), permanent crops (vineyards, fruit trees, and berry plantations), pastures, and heterogeneous agricultural areas (complex cultivation patterns and mixed agriculture and natural vegetation).

## 4. Methodology

There are 3 major steps required for accurately measuring land-use/land-cover change using satellite imagery: (1) image preprocessing, (2) selection of change detection method, and (3) accuracy assessment (Lu et al. 2004). The data analysis flow chart in Figure 2 shows how each of these steps were conducted for this study and is described in detail below.

### *4.1. **Image preprocessing***

4.1.1 **Scene registration and cloud mask construction.** For the image preprocessing, all scenes were co-registered to a base scene and converted to a common grid. This was accomplished using manually selected tie points between sets of images such as river junctions, bridges over rivers, and road junctions. Several bridge tie points were unusable since they were among the 50 some bridges destroyed during the war (Europe for BiH 1999) and had been rebuilt adjacent to the original structure.

For both sets of scenes, the Landsat 7 ETM+ scenes from the University of Maryland were used as the base scenes to which all other scenes were registered. These Maryland scenes had been orthorectified and georegistered as part of the Landsat GeoCover project at the Global Land Cover Facility. Good registration accuracies within ½ pixel were achieved for all scenes except the July 1994 scene (Table 3), though visually this registration was quite good over the study area portion of the scene. No registration was performed on the September 1992 scene since it is also from the University of Maryland's GeoCover dataset.

Additional pre-processing for the analyses required generating cloud masks for both the west and east sets of scenes by manually setting thresholds for clouds and cloud shadows (Table 3). Band 1 (blue) best discriminated white cloud tops from surrounding vegetation and band 5 (mid-IR) performed well for detecting cloud shadows. Band 1 provides the best separation between cloud tops and vegetated land because clouds are most reflective at these shorter wavelengths (>70%) while vegetation reflects poorly (<15%) in the blue spectrum (Jensen 2000). Cloud shadows are more difficult to detect since dark areas can be confused with topographic shadows and other dark features. Band 5 was selected based on its good visual separation between the land surface and dark shadows. Master cloud masks were generated by combining the individual masks for each set of scenes.

4.1.2 **Radiometric scene normalization**. The necessity for controlling radiometric noise (sensor degradation, change in solar illumination, atmospheric scattering and absorption, and changes in atmospheric conditions such as water vapor density and cloud cover) depends on the method of detecting change. For techniques that do not directly compare digital numbers (e.g. post-classification comparison) or only apply linear transformations (e.g. simple image/band differencing), atmospheric correction is not necessary. In contrast, methods that use band ratios (e.g. most vegetation indices such as the normalized difference vegetation index (NDVI) and the simpler NIR/red ratio) are contaminated by atmospheric effects and should be corrected before computing the ratios (Song et al. 2001).

Since radiative transfer codes are not available for the Landsat imagery used here, only relative radiometric normalization methods were considered. Relative radiometric normalization relies on selecting a stable set of pixels from two images that can be used to construct a linear relationship for each pair of radiometric bands. Manual selection of these pseudo-invariant features (PIFs) often rely on built features such as roads, urban areas and industrial centers for use as control points (Schott et al. 1988, Hall et al. 1991). This method, however, is not appropriate for areas that lack spectrally stable bright and dark ground features (Kaufmann 2001). In addition to the errors associated with manually selecting PIFs, applying the method to BiH is problematic due to altered spectral signatures from wartime damage to buildings and roads.

Instead, methods that use the statistical properties of images to automate the process of identifying no-change pixels were favored. Du et al. (2002) use bivariate principal components analysis between the same bands to select stable pixels, but their method requires the user to select a threshold in determining the set of pixels. Instead, the fully automated multivariate alteration detection (MAD) method developed by Nielsen et al. (1998) and Canty et al. (2004) was used. The MAD method seeks to transform each group (before and after images) of bands such that the variance of the transformed band differences is maximized. This is done using a canonical correlation analysis between the two groups of variables (bands). Then, using a probability threshold, no-change pixels are selected for use in the radiometric normalization. Instead of ordinary least squares regression, the authors recommend orthogonal regression to calculate the linear relationship between bands since it does not assume that the measured variables are error-free. Since this method is invariant to linear transformations of the original image, it is not necessary to perform a top of the atmosphere calibration on the raw data. This method has the advantage of full objectivity and reproducibility. The normalized Landsat scenes can then be used to calculate an NDVI for detection of vegetation changes.

An alternative approach specific to change detection studies avoids explicitly creating radiometrically normalized images by relying instead on the ordinal conversion of a single band in the imagery (Nelson et al. 2005). By ranking an individual band sensitive to vegetation health (e.g. the near-infrared band) and then subtracting the bands, change thresholds can be set around the mean, with pixels exhibiting the largest changes moving up or down the most in the rankings.

This research used both Nelson et al.'s (2005) rank difference method and Canty et al.'s (2004) MAD method (Figure 2). Both methods do not require areal photographs or other sources of ground reference information.

### 4.2 ***Methods for detecting land-use/land-cover change***

There are dozens of different remote sensing change detection techniques applicable to land-use/land-cover studies (Lu et al. 2004). Multiple reviews and comparisons of these methods have been conducted with little agreement on an optimal method (Singh 1989, Mas 1999, Dhakal et al. 2002, Coppin et al. 2004, Lu et al. 2004). The methods used in this study are simple algebraic differencing, supervised classification, and the multivariate alteration detection (MAD) transformation.

The techniques within the algebra category have the advantage of being simple to implement, though they are not capable of providing complete 'from-to' matrices of class change information. Within this group, the most widely used change detection technique is univariate image differencing. For the algebraic differencing, two images are subtracted and change pixels are selected by setting thresholds at the tails of the resulting distribution. This popular method (Singh 1989, Coppin et al. 2004) often uses NDVI ratios to highlight differences in vegetation (Serneels et al. 2001, Nordberg and Evertson 2005). For northeast Bosnia, abandoned land pixels are expected to exhibit higher NDVI values in contrast to the pre-war NDVI values which are suppressed by the absence of vegetation near the sowing and harvesting time.

The multivariate alteration detection (MAD) method used to radiometrically rectify images can also be used to detect change. Whereas in the rectification process it seeks to isolate stable ‘no-change’ pixels, it can just as easily be used to select maximum change areas since its goal is to find linear combinations of the original bands that give maximal multivariate differences. The key is to choose linear coefficients that minimize the correlation between the resulting combined images such that the difference between the two images is maximized. Again, canonical correlation analysis is used to determine the transformation vectors. This MAD change detection method has the advantage of being invariant to linear scaling, thereby eliminating the need to apply any atmospheric corrections to the data.

Though post-classification change detection methods are frequently used to detect change, a full classification of before and after images was not possible since no training data are available for the pre-war imagery and collecting ground reference data for categories such as forests in BiH is too dangerous due to the uncertain presence of landmines and unexploded ordnance. Instead, a single classification using the complete time series of NDVI values was created to exploit the relatively rich temporal dimension of the satellite imagery (Table 2). This approach has the advantage of incorporating seasonal vegetation changes over the growing period. In particular, the minimum distance classifier was used since it produced classifications with fewer noise pixels than other supervised classifications. The minimum distance classifier uses the Euclidean distance between each pixel and the vector mean of the training data (Richards and Jia 1999). Training data for areas of abandoned agricultural land were selected from fine resolution Quickbird imagery (60 cm pansharpened) available in Google Earth.

To summarize, four change-detection procedures were applied to the Landsat scenes covering the study area:

1) simple difference of NDVI values (average of spring & summer scenes) using MAD method of radiometric rectification (Canty et al. 2004)
2) simple difference of ranked summer band 4 (Nelson et al. 2005)
3) multivariate alteration detection (MAD) change detection.
4) phenological variation based on NDVI variation: an automation of Terres et al. (1999) by selecting pixels that exhibit shifts from active agriculture to abandoned agriculture for use in a supervised classification

The simple difference methods require a change threshold to be set based on the statistical distribution of pixel values. To help isolate agricultural changes, these thresholds were set after the mask of agricultural and pasture land from the Corine Land-Cover (CLC) 100 m dataset (EEA 2000) was applied. This eliminates the greater spectral variation found in forests and urban areas from the analysis. Thresholds of 1.5 and 2.0 standard deviations from the mean were used to identify significantly changed pixels. Results from these methods were compared before selecting the best method for quantitative validation.

### 4.3 *Ground reference data and classification verification*

The challenge of collecting ground reference data is especially problematic when using historical remote sensing data for which first hand observations are not possible. Sometimes aerial photographs (Lo and Faber 1997, Lambin 2003, Dahdouh-Guebas et al. 2004, Romero-Calcerrada and Perry 2004) and retrospective postal surveys (Baban and Luke 2000) can be used , but this was not the case in BiH. Though BiH was highly photographed during the war, most of these images are not accessible to the public and are still classified by the US government. Retrospective surveys were also not practical since most farms are very small with poor records, many residents have yet to return to the land they once occupied, and the ownership of much of the land is still in dispute meaning respondents would be very reluctant to answer such sensitive questions.

Instead, ground reference data was collected after the data analysis was completed similar to Serneels et al. (2001) and Nordberg and Evertson (2005). Since minefields still effectively restrict access to much of the land in BiH, only land parcels visible from roads or well-worn farm pathways were visited as part of the field work. The final classified image was used to select 150 'abandoned land' sites and 100 'active agriculture' sites using a stratified random sampling approach. These numbers were chosen since guidelines call for collecting a 75-100 samples per category for study areas larger than 1 million acres (McCoy 2005). In the BiH study area, there are almost 2 million acres of agricultural land. Also, since the expectation is that there is more cultivated land than abandoned land, 'abandoned land' sites were disproportionately sampled to ensure that the smaller category (by area) is not misclassified (Khorram 1999).

The city of Tuzla (Figure 1) was used as a 'base camp' for day trips to field locations. Sample field site coordinates were uploaded to a GPS receiver that was then used to locate the points. A road map of BiH, digital road network, and printed Google Earth maps (both Terra Metrics 15 m and Quickbird 60 cm) were used to help navigate to the field sites. In a few instances, local residents were nearby to discuss the historical land use of the field site.

## 5. Results

### *5.1* ***Band 4 rank difference***

The rank difference change detection method followed that of Nelson et al.'s (2005) study. The implementation used for this study ranked each of the input bands, subtracted them, and then selected pixels greater than 1.5 and 2.0 standard deviations from the difference mean. This process was performed on band 4 (near-infrared wavelength) for the pre-war and most recent scenes whose acquisition dates were closest in terms of the annual growing season. For the west scenes, the ranked band 4 from September 14th of 1992 was subtracted from the ranked band 4 from August 30th of 2004. Similarly, the ranked near-infrared band from the east scenes on June 17th 1991 was subtracted from its counterpart band from May 22nd 2005. Nelson et al. use band 4 due to its greater sensitivity to vegetation health.

These results proved disappointing in detecting abandoned agricultural land. In some areas, large agro-industrial fields (e.g. Bosanska Gradiska, western scenes) were detected as abandoned. But since these areas were not severely affected by the war, the large, uniform changes detected are most likely due to spectral differences associated with different plowing and harvesting dates between the two years. In other areas, riparian zones prone to flooding and rapid changes associated with moisture fluxes were detected. Also, known areas of abandoned land in the Brčko district were not detected (Figure 3). These results also showed a great deal of noise pixels not associated with any rectilinear agricultural fields.

Nelson et al's method is attractive for its simplicity and ease of implementation since it requires no radiometric normalization but, like with all methods, has limitations. So while it worked well for the authors in detecting forest changes (especially cut areas) in British

Columbia, it was not able to detect the more subtle changes that occurred in the agricultural land of BiH.

### *5.2 MAD radiometric rectification and NDVI difference*

Next, the simple difference method between the normalized difference vegetation index (NDVI) for two dates was tested. Before calculating the NDVI for the pre- and post-war imagery, the six non-thermal bands for all scenes were radiometrically rectified using Canty et al.'s (2004) multivariate alteration detection (MAD) transformation method. This step is required since the NDVI ratio is sensitive to atmospheric differences both between scenes and bands within scenes (Song et al. 2001). Since the rectangular box containing the study areas was too large to apply the MAD rectification (5741 x 4036 pixels for the west scenes, 4663 x 4782 pixels for the east scenes), a subset region of 2500 x 2500 pixels was selected for each set of scenes. These regions were selected such that there was a representative mix of water, agricultural land, and forest land. Normalization parameters were then calculated for these subset regions and applied to the entire study area.

For each set of scenes, all scenes were normalized to a single base scene which was selected according to the scene's quality and distribution of digital numbers. In particular, high means and large standard deviations in bands 3 and 4 were sought to prevent a reduction in the radiometric resolution of the normalized scenes. Additionally, scenes with large amounts of cloud cover were excluded from consideration as the base scene. For the west set of scenes, the May 26th, 2004 scene was used as the reference image and for the east set of scenes, the July 25th, 2005 scene was used (Tables 4 and 5).

Tables 4 and 5 show the results from the MAD normalization for both sets of scenes. The Total Mean column shows the band means for all pixels in the study area. The MAD Region Test Pixels Means column is for the means of 1/3 of the test pixels that were withheld from the total number of 'no-change' pixels (which in turn were selected from the 2500 x 2500 pixel study area subset). Since these stable 'no-change' pixels differ for each normalization calculation, the means for the reference scene vary by one to two digital numbers (DNs). The corresponding *t*-test for equal means shows that all but three bands have statistically equal means at the 5% confidence level. For the April 1990, August 1994, and May 2005 scenes, the band 4 means are not statistically equal, possibly due to the greater sensitivity of the near-infrared spectrum to changes in vegetation.

After completing the radiometric normalization, NDVI values were calculated for all scenes. This provides a directly comparable measure of vegetation health at each time slice. One advantage to this approach is that average NDVI values can be calculated from the spring and summer scenes. By averaging the spring and summer scene NDVI values, intra-annual variation associated with planting and harvesting is reduced, thereby aiding in the detection of long-term changes.

Figure 4 shows the results from this differencing for the east set of scenes for the difference between average NDVI values from 1991 and 2005. Pixels greater than 2.0 standard deviations from the mean are shown in gray after some simple post classification steps were applied. Specifically, speckles and holes in the image were reduced by first clumping the change pixels using a 3x3 filter, and then sieving these results by considering the eight neighboring pixels and removing groups with less than four pixels.

Results from this method appear to be better than the ranked difference results above, but there are still a considerable number of noise pixels detected as abandoned land. The larger rectilinear areas identified as abandoned agricultural land coincide with known abandoned fields, but many of the smaller specs are simply noise pixels at the edges of fields or streams (zoomed box of Figure 4).

### *5.3* ***MAD change detection***

For the multivariate alteration detection (MAD) algorithm, three bands from the pre- and post-change images were used as inputs. To focus on vegetation changes, for both the west and east sets of scenes, bands 3-5 were used for scenes acquired during a similar point in the growing season. For the west scenes, the images from April 1990 and May 2004 were used since they lack any substantial cloud cover. For the east scenes, the June 1991 and May 2005 images were used. A temporal approach was also tested by using the band 4s from the first three dates (1990-1994) as the first image and latter band fours (1999-2005) as the second image. Change thresholds for each band were determined automatically to minimize the misclassification error (Canty and Nielsen 2006).

Results from these analyses struggled to detect areas of abandoned agricultural land. This occurred for several reasons. A significant hindrance was the inability to mask out clouds, cloud shadows, and non-agricultural land. As a result, clouds and cloud shadows dominated the resulting change images. Also, features with greater reflectance changes dominated the results. For instance, active agricultural fields and rivers which are subject to rapid fluctuations following severe rain events and seasonal variation were clearly visible. Figure 5 shows representative results of these analyses for bands 3-5 of June 1991 and May 2005, east scenes.

Though the MAD variates have the potential to differentiate seasonal vegetation changes and image noise from smaller scale anthropogenic changes (Canty 2006), for this dataset, the presence of clouds limited its ability to detect more subtle vegetation changes. Its ability to detect multiple directions of change means that future implementations that do support cloud and land cover masking are likely to significantly improve its ability to detect abandoned agricultural land.

### *5.4* ***Minimum distance supervised classification***

The final change detection method uses a supervised classification approach. DigitalGlobe Inc.'s fine resolution 60 cm Quickbird data available via Google Earth provided the input data required to train the classifier. These fine resolution scenes were acquired by the satellite in 2003 and 2005 and provided online as pansharpened images (Table 6). These pansharpened images are of sufficient resolution to identify the uneven texture of abandoned agricultural land in contrast to the uniform conditions found over active agricultural land.

Four training sets representing different areas of abandoned agricultural land, each containing 50-300 pixels, were selected for both sets of Landsat scenes. These training sets were then used to detect abandoned agricultural land based on NDVI values from the six time slices of Landsat imagery. Since direct comparison between NDVI values was not necessary, the raw DNs were used to calculate the NDVI for each scene. Multiple supervised classifiers were applied (results not presented for parallelpiped, Mahalanobis, maximum likelihood, and spectral angle mapper classifiers), with the minimum distance classifier performing best, generating the fewest number of obvious noise pixels. Since only one category was classified from the CLC agricultural land subset, a maximum three to six standard deviations from the mean vector of the training data was used to classify the pixels.

The results from both sets of scenes were combined into a single map of abandoned agricultural land. Figure 6 shows the results from the eastern set of scenes. This map of abandoned land was also ‘cleaned’ similar to the normalized NDVI difference map above, with the same clumping and sieving algorithms applied to reduce noise pixels. The minimum distance classification was the best classifier based on its relatively few noise pixels and good detection of known abandoned land in Brčko.

Once the west and east scene results were merged, the area of abandoned land for each study area *opstina* was calculated. This was done by overlaying the *opstina* borders onto the Landsat pixel data and applying the zonal sum function to calculate the total area of abandoned agricultural land in each *opstina* zone. Figure 7 shows the resulting detected abandoned agricultural land as a percentage of agricultural land for each district. Districts along the northern border with Croatia experienced more abandonment than the more forested regions in the southern portion of the study area. The greatest amount of abandoned agricultural land was found in the Brčko district. These areas of greater abandoned agricultural land are generally associated with more intense fighting, especially in Brčko which was a highly contested region during the war.

An accuracy assessment of the map was conducted using ground reference data collected during May of 2006. This time period was chosen to coincide with the initial vegetation green-up. Abandoned and active agricultural survey sites were selected from the supervised classification results using a stratified random sample of 150 abandoned land sites and 100 active agricultural land sites (Figure 8). The resulting spatial distribution spans nearly the entire study area with survey sites on both sides of the Inter-Entity Boundary Line (IEBL). The higher concentration of abandoned agricultural land survey sites in the northeast portion of the study area reflects the high concentration of abandoned agricultural land detected there. Risk of landmines restricted access to many sites that were not within sight of traveled dirt roads.

A second source of reference data was the fine resolution Google Earth Quickbird imagery. No reference data that overlapped with the input training data were used to assess the map accuracy. Additional Quickbird imagery became available in Google Earth between creation of the abandoned agricultural land classification and verification of its accuracy. Table 7 lists these additional scenes as of October 2006.

Table 8 presents the three error matrices derived from the field ground reference data, Quickbird imagery, and a combined matrix using both datasets. The producer’s accuracy is calculated from the respective column totals in each matrix, the user’s accuracy from the row totals, and the total accuracy down the diagonal.

The accuracies for the abandoned land category are consistent across all three matrices and remain above 81%, while the non-abandoned category accuracy is less stable and drops below 70% for the producer’s accuracy. The overall accuracy is consistent for all matrices, ranging from 81% to 85%, which compares favorably to the industry average of 76% classification accuracy over the last 15 years (Wilkinson 2005). All three matrices have Z statistics well above 1.96 indicating that the classification is significantly better than random at the 95% confidence level.

These tables show that false positives (commission errors) for abandoned agricultural land are more common than false negatives (omission errors), meaning some areas classified as abandoned land were actually engaged in active agricultural practises. In some cases, the land was currently being used for grazing livestock and was mistakenly identified as abandoned. For other cases, especially in Brčko, the land had recently been returned to production, causing a mismatch between the satellite imagery and the field reference data. This was revealed in one instance during an interview with members of a Brčko farmers cooperative identified non-abandoned agricultural land on a printed map of the area.

Other interviews during May of 2006 indicated there was also additional abandoned land that remained undetected. Hamid Čustović, Professor of Agriculture at the University of Sarajevo, singled out Derventa for its large area of abandoned agricultural land. This was seen firsthand when driving through Derventa, a district that experienced heaving fighting and was subjected to domicide practises (deliberate destruction of homes and monuments) during the war (Ó Tuathail and Dahlman 2006). To the east, Marko Blagojević, Director of Agrokoperative in Bratunac, noted there were large areas of abandoned land in Srebenica and Bratunac, a region known for its orchards and berry production. These regions of undetected abandoned agricultural land are characterized by hilly terrain and small agricultural plots interspersed with forest. Such mixed land use (e.g. Figure 9) is difficult to discriminate due to pixel mixing in the Landsat imagery.

Variable vegetation response in abandoned agricultural areas also hindered the change detection classification. Edges of fields bordering forests, for instance, tended to have medium-size trees (3-4 m) while central portions of the same fields were often covered by weeds and grasses about 1 m in height, similar in appearance to mature wheat (Figure 10). This resulted in good identification of abandoned agricultural land in areas dominated by relatively large, homogenous agricultural fields. Abandoned agricultural land missed by the classification occurred in hilly terrain with heterogeneous land cover. The Landsat analyses demonstrate that detecting decadal long increases in vegetation are possible using 30 m multispectral imagery.

Further analysis of the results from the accuracy assessment (Table 8) demonstrates the viable use of Quickbird imagery as an alternative form of ground reference data. Formally, the Z-score between the field matrix and Quickbird matrix is 1.18, meaning there is no statistical difference between the two matrices at the 95% confidence level. This has implications for future research that requires ground reference data in hard to reach or dangerous places. For study areas with ongoing wars that are more dangerous than BiH (e.g. Darfur), careful use of Quickbird imagery coupled with knowledge of the local land use practises should greatly expand researchers' ability to conduct accuracy assessments for satellite imagery in these dangerous regions.

## 6. Conclusions

The analysis tested four different change detection methods: rank differencing, NDVI differencing after radiometric normalization, multivariate alteration detection (MAD), and supervised classification. The first two methods of simple differencing rely on a single observation for the initial time period and another observation for the end time period. This constraint prevented them from exploiting the full temporal dimension of the dataset and yielded disappointing results, even over the relatively long time period from 1991 to 2005. The MAD method was also limited by data inputs and the inability to mask out clouds from the analysis which prevented a more focused analysis. In contrast to these methods, the supervised classification was able to exploit the full temporal dimensions of all six Landsat scenes for both path/rows.

In other comparisons of change detection methods, supervised classifications have also performed well (Mas 1999), but most change detection methods that use supervised classifications do not apply the method in the multi-date fashion employed here. Instead, it is more common to see post-classification comparisons, where the initial image and end image are classified separately using independent training data (Mas 1999, Petit et al. 2001, Lu et al. 2004). The absence of pre-war training data prevented the use of such a post-classification change detection method here.

This research demonstrates the viability of detecting land-cover changes in post-war zones. The lack of such war-related research that uses remote sensing data as a component of analysis means that the methods used here can serve to broaden the existing approaches to war impact studies. Assessing these impacts, however, is greatly hampered by a lack of pre-war baseline data.

Another implication from this research stems from the effective use of fine resolution Quickbird imagery as an alternative source of ground reference data. The use of freely available Quickbird imagery online in conjunction with ground reference data shows that for land-use/land-cover changes identifiable at the 60 cm pixel size, the Quickbird imagery is a viable alternative to expensive and sometimes dangerous ground reference data collection. As more data become available online, the possibilities for using these data in this way will expand.

Remote sensing technology is an important tool in providing both pre-war and post-war assessments on the impacts of war. Though data from this technology are not capable of a complete environmental assessment of factors such as air quality, wildlife health, or soil pollutants, they can provide valuable information on changes in vegetation. By using remote sensing and GIS technology to integrate the social and environmental impacts from war, a better understanding of how these complex systems interrelate can be achieved. Results specific to agriculture can help reduce dependence on food imports by identifying the spatial extent of regions that were especially hard hit by conflict and can benefit from more targeted international aid.

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## Tables

**Table 1.** General crop calendar for continental Bosnia-Herzegovina.

| Crop | Sow (month) | Harvest (month) |
|---|---|---|
| Wheat (*Triticum vulgare*) | X | VI, VII |
| Rye (*Secala cereale*) | IX, X | VI, VII |
| Winter barley (*Hordeum vulgare*) | X | VI, VII |
| Spring barley (*Hordeum vulgare*) | III | VII |
| Winter oats (*Avena sativa*) | IX, X | VI, VII |
| Spring oats (*Avena sativa)* | III | VII, VIII |
| Maize (*Zea mays*) | IV, V | IX, X |
| Common Millet (*Panicum miliaceum)* | IV, V | VIII |
| Sorghum Millet (*Sorghum vulgare)* | IV, V | VIII, IX |
| Rice (*Oryza sativa*) | IV, V | VIII |
| Sunflower (*Helionathus annuss*) | IV | VIII, IX |
| Soy Bean (*Lycine hispida)* | IV | VIII, IX |
| Oil Rape (*Brassica naous*) | IX, III | VI, VII |

**Table 2.** Landsat scenes used for the analysis.

| Path 188, Row 29 | | | Path 187, Row 29 | | |
|---|---|---|---|---|---|
| **Acquisition Date** | **Clouds (%)** | **Sensor** | **Acquisition Date** | **Clouds (%)** | **Sensor** |
| 4/02/1990 | 0 | TM | 6/17/1991 | 0 | TM |
| 9/14/1992 | 0 | TM | 9/05/1991 | 10 | TM |
| 7/18/1994 | 0 | TM | 8/28/1994 | 10 | TM |
| 9/26/1999 | 0 | ETM+ | 8/20/2000 | 0 | ETM+ |
| 5/26/2004 | 2 | TM | 5/22/2005 | 32 | TM |
| 8/30/2004 | 15 | TM | 7/25/2005 | 15 | TM |

**Table 3.** Image registration root mean square error (RMSE) values (measured in pixels) and cloud/cloud shadow threshold values in raw digital numbers (DN). Pixels outside the thresholds were excluded from the analysis.

| West Scenes | Registration RMSE | TM Band | Min DN | Max DN | East Scenes | Registration RMSE | TM Band | Min DN | Max DN |
|---|---|---|---|---|---|---|---|---|---|
| 4/2/1990 | 0.34 | 1 | no clouds | | 6/17/1991 | 0.46 | 1 | no clouds | |
| | | 5 | | | | | 5 | | |
| 9/14/1992 | -- | 1 | no clouds | | 9/5/1991 | 0.41 | 1 | 1 | 120 |
| | | 5 | | | | | 5 | 17 | 255 |
| 7/18/1994 | 1.13 | 1 | no clouds | | 8/28/1994 | 0.47 | 1 | 1 | 110 |
| | | 5 | | | | | 5 | 19 | 255 |
| 9/26/1999* | -- | 1 | no clouds | | 8/20/2000* | -- | 1 | 1 | 125 |
| | | 5 | | | | | 5 | 25 | 255 |
| 5/26/2004 | 0.47 | 1 | no clouds | | 5/22/2005 | 0.38 | 1 | 1 | 155 |
| | | 5 | | | | | 5 | 30 | 255 |
| 8/30/2004 | 0.37 | 1 | 1 | 80 | 7/25/2005 | 0.22 | 1 | 1 | 120 |
| | | 5 | 18 | 255 | | | 5 | 21 | 255 |

*Register to this scene.

**Table 4.** Comparison of means for hold-out test pixels in bands 3 and 4 of the path 188 row 29 (west) scenes before and after MAD normalization. Results from the paired *t*-tests for equal means are also shown.

| West Scenes | TM Band | Total Mean | MAD Region Test Pixels Mean | Normalized Mean | *t*-value | *p*-value |
|---|---|---|---|---|---|---|
| 4/2/1990 | 3 | 28.35 | 26.60 | 22.36 | -0.327 | 0.740 |
| | 4 | 50.74 | 50.91 | 106.49 | 2.254 | 0.024 |
| 9/14/1992 | 3 | 24.55 | 22.59 | 21.45 | -0.105 | 0.923 |
| | 4 | 60.01 | 61.05 | 107.11 | -1.216 | 0.224 |
| 7/18/1994 | 3 | 24.83 | 21.55 | 20.57 | -0.338 | 0.741 |
| | 4 | 89.36 | 90.37 | 108.56 | -0.389 | 0.689 |
| 9/26/1999 | 3 | 38.45 | 35.01 | 21.18 | 1.781 | 0.075 |
| | 4 | 90.28 | 92.03 | 107.89 | -0.189 | 0.842 |
| 5/26/2004* | 3 | 25.79 | 20.56 to 22.36 | -- | -- | -- |
| | 4 | 101.78 | 106.60 to 108.553 | | | |
| 8/30/2004 | 3 | 23.15 | 18.93 | 20.78 | 0.622 | 0.532 |
| | 4 | 77.00 | 75.10 | 107.58 | -1.544 | 0.123 |

*Radiometrically normalize to this reference scene.

**Table 5.** Comparison of means for hold-out test pixels in bands 3 and 4 of the path 187 row 29 (east) scenes before and after MAD normalization. Results from the paired *t*-tests for equal means are also shown.

| East Scenes | TM Band | Total Mean | MAD Region Test Pixels Mean | Normalized Mean | *t*-value | *p*-value |
|---|---|---|---|---|---|---|
| 6/17/1991 | 3 | 34.47 | 24.76 | 19.60 | 0.658 | 0.511 |
| | 4 | 108.60 | 112.88 | 95.40 | 0.427 | 0.661 |
| 9/5/1991 | 3 | 30.05 | 23.03 | 20.44 | 0.155 | 0.847 |
| | 4 | 75.78 | 72.82 | 96.37 | 0.823 | 0.406 |
| 8/28/1994 | 3 | 27.37 | 20.47 | 20.69 | 0.322 | 0.748 |
| | 4 | 72.38 | 73.91 | 97.33 | 3.076 | 0.002 |
| 8/20/2000 | 3 | 59.01 | 50.00 | 20.42 | -0.785 | 0.436 |
| | 4 | 77.00 | 78.31 | 95.61 | 0.818 | 0.412 |
| 5/22/2005 | 3 | 29.91 | 21.31 | 19.92 | 0.785 | 0.428 |
| | 4 | 102.46 | 112.69 | 95.12 | -2.654 | 0.008 |
| 7/25/2005* | 3 | 24.99 | 19.61 to 20.69 | -- | -- | -- |
| | 4 | 96.02 | 95.09 to 97.38 | | | |

*Radiometrically normalize to this reference scene.

**Table 6.** Quickbird scenes available in Google Earth as of May 2006.

| Location | Acquisition Date | Cloud Cover | Catalog ID | Pan-Resolution (m) | Multi-Resolution (m) |
|---|---|---|---|---|---|
| Brčko | 03/24/2003 | 0% | 1010010001BDBD01 | 0.65 | 2.59 |
| Bratunac | 03/29/2003 | 2% | 1010010001C10A01 | 0.65 | 2.58 |
| Srebrenica | 03/29/2003 | 6% | 1010010001C10A02 | 0.65 | 2.59 |
| Doboj | 04/03/2003 | 0% | 1010010001C56301 | 0.64 | 2.58 |
| Bijeljina | 05/12/2003 | 0% | 1010010001E43B01 | 0.64 | 2.58 |
| Bosanski Brod | 07/07/2005 | 0% | 10100100045AF701 | 0.63 | 2.52 |
| Tuzla | 07/25/2005 | 0% | 101001000465C001 | 0.62 | 2.49 |
| SE of Tuzla | 07/28/2003 | 0% | 101001000224BE01 | 0.64 | 2.54 |
| Prnjavor | 09/17/2005 | 1% | 1010010004871401 | 0.61 | 2.45 |
| S of Prnjavor | 09/17/2005 | 2% | 1010010004871402 | 0.61 | 2.46 |

**Table 7.** Additional Quickbird scenes available in Google Earth as of October 2006. New Tuzla scene replaces the one listed in Table 6.

| Location | Acquisition Date | Cloud Cover | Catalog ID | Pan-Resolution (m) | Multi-Resolution (m) |
|---|---|---|---|---|---|
| Orasje | 03/24/2006 | 0% | 1010010004E20010 | 0.64 | 2.55 |
| Maoca/Brčko | 03/24/2006 | 0% | 1010010004E20011 | 0.64 | 2.56 |
| N of Tuzla | 03/24/2006 | 7% | 1010010004E20012 | 0.64 | 2.58 |
| Tuzla | 03/24/2006 | 4% | 1010010004E20013 | 0.65 | 2.59 |
| Bosanska Gradiska | 06/27/2006 | 0% | 10100100050CE00E | 0.62 | 2.46 |
| S of Bos. Gradiska | 06/27/2006 | 0% | 10100100050CE00F | 0.62 | 2.46 |
| N of Banja Luka | 06/27/2006 | 0% | 10100100050CE010 | 0.62 | 2.46 |
| Banja Luka | 06/27/2006 | 0% | 10100100050CE011 | 0.62 | 2.46 |

**Table 8.** Error matrices based on field reference data and Quickbird imagery.

| Classified Data | Field Ref. Data | | | Quickbird Ref. Data | | | Combined Ref. Data | | |
|---|---|---|---|---|---|---|---|---|---|
| | AB | NA | Total | AB | NA | Total | AB | NA | Total |
| AB | 49 | 11 | 60 | 72 | 15 | 87 | 88 | 20 | 108 |
| NA | 2 | 22 | 24 | 6 | 19 | 25 | 5 | 30 | 35 |
| Total | 51 | 33 | 84 | 78 | 34 | 112 | 93 | 50 | 143 |

| | Field Ref. Data | | Quickbird Ref. Data | | Combined Ref. Data | |
|---|---|---|---|---|---|---|
| | Producer's accuracy | User's accuracy | Producer's accuracy | User's accuracy | Producer's accuracy | User's accuracy |
| AB = | 96.1 | 81.7 | 92.3 | 82.8 | 94.6 | 81.5 |
| NA = | 66.7 | 91.7 | 55.9 | 76.0 | 60.0 | 85.7 |
| Total accuracy = | 84.5 | | 81.3 | | 82.5 | |
| Z statistic = | 8.0 | | 6.2 | | 8.5 | |

Land Cover Categories: AB = Abandoned NA = Non-Abandoned

## Figures

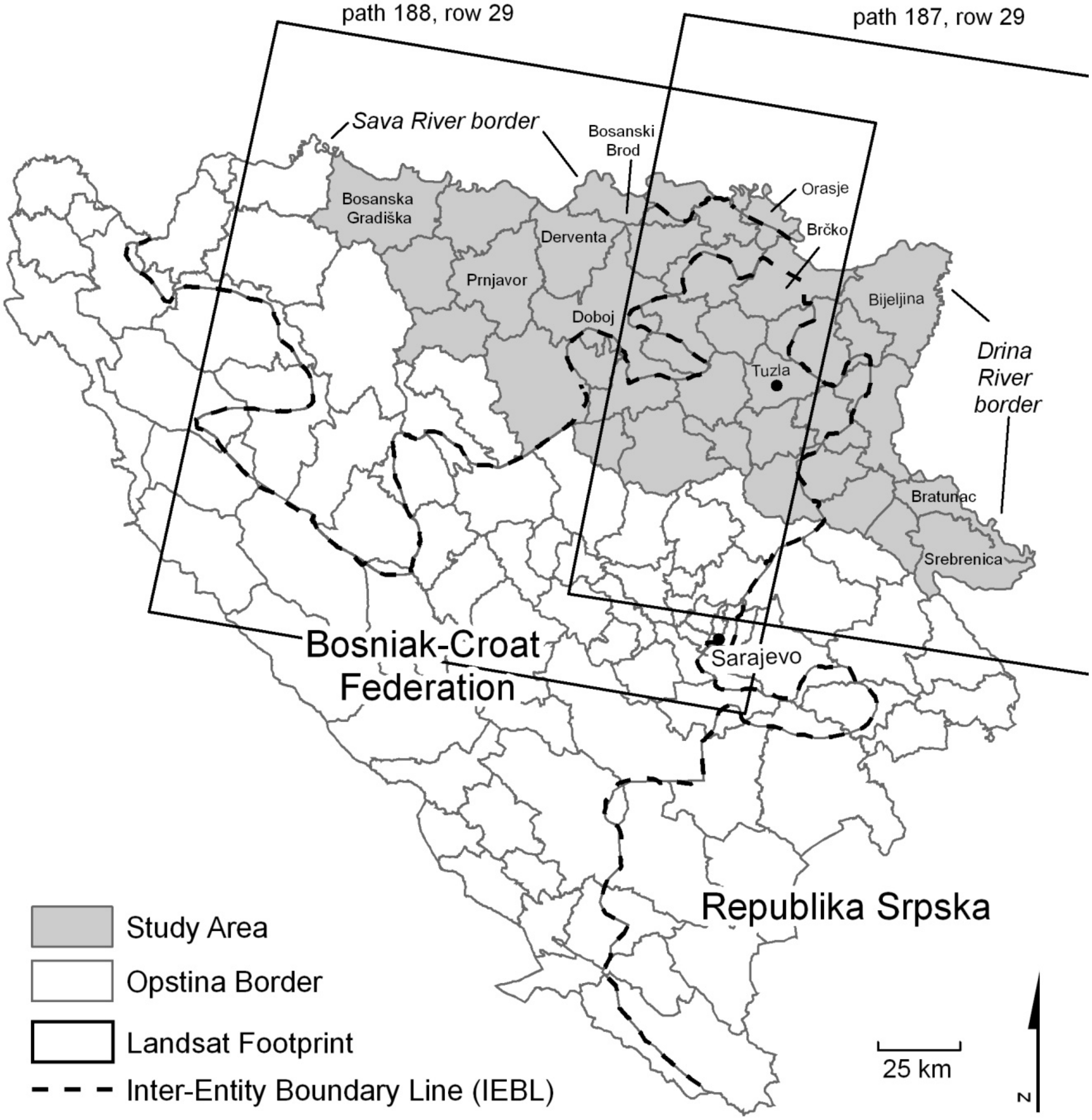

**Figure 1.** Bosnia-Herzegovina *opstini* in the study area, selectively labeled with pre-war names. West (path 188, row29) and east (path 187, row29) Landsat scene footprints also shown.

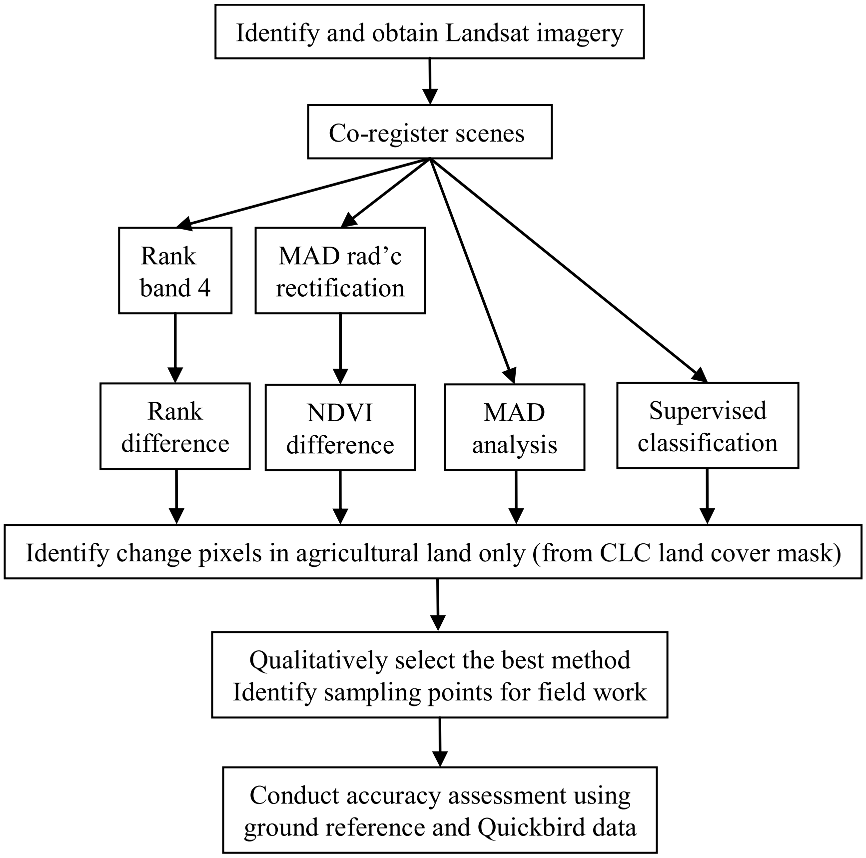

**Figure 2.** Data analysis flow chart. The MAD acronym, multivariate alteration detection, is described below.

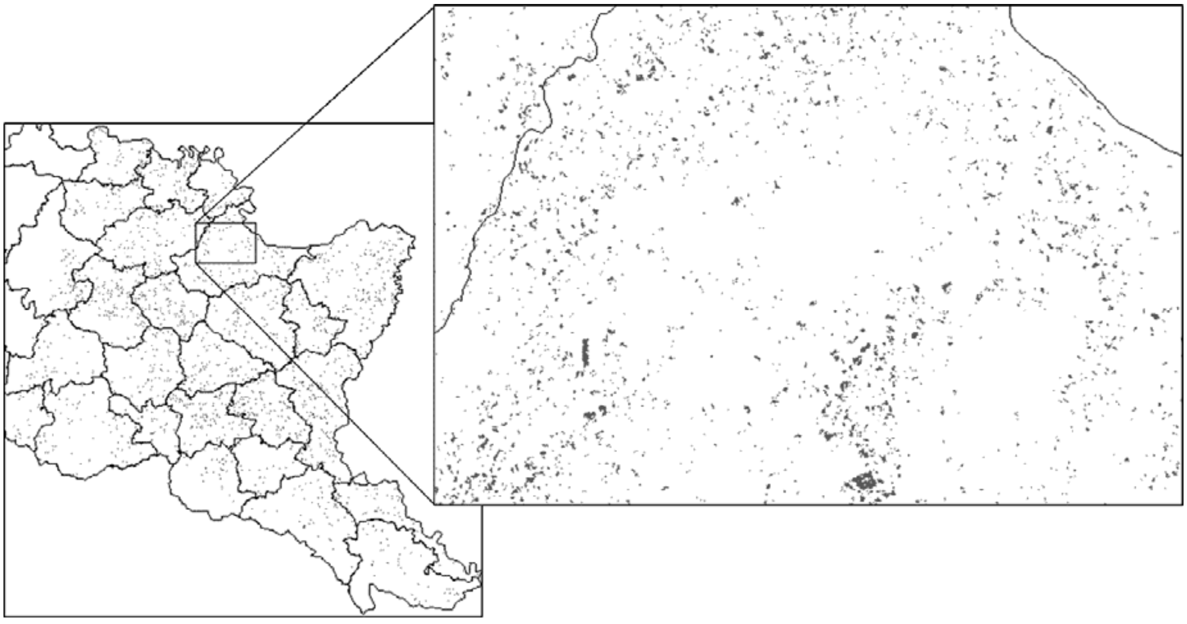

**Figure 3.** Rank difference results for the east scenes of the study area, June 1991 subtracted from May 2005. Pixels greater than 2.0 standard deviations from the mean are shown in gray. Zoomed box is the primarily agricultural region of Brčko.

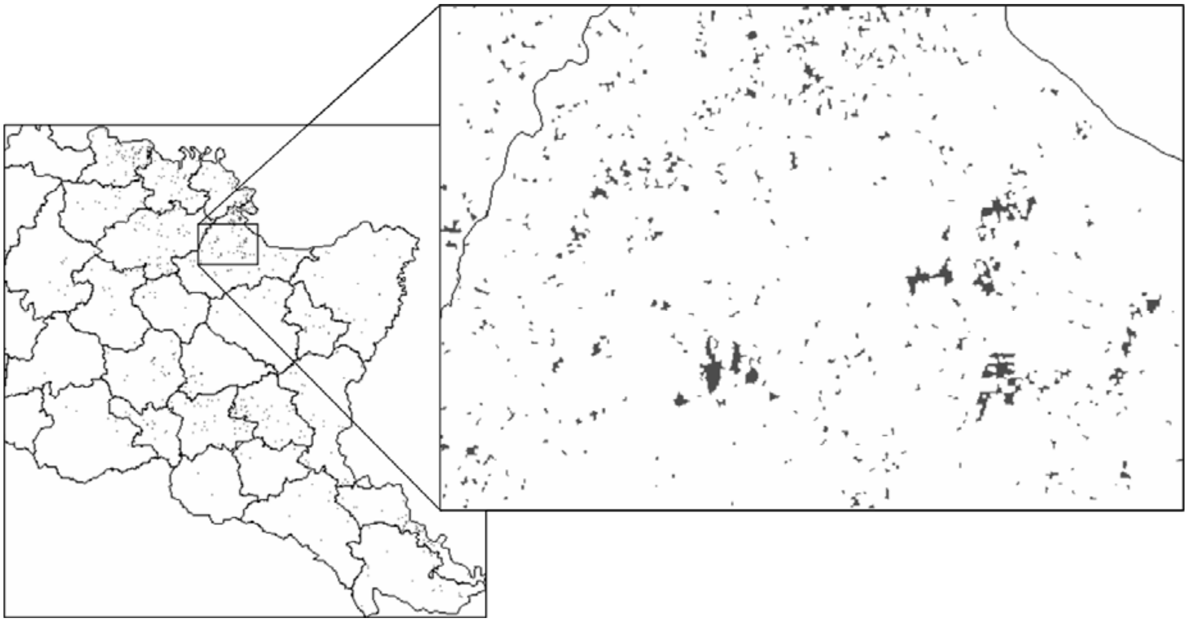

**Figure 4.** Normalized average NDVI difference east scene of the study area, 1991 subtracted from 2005. Pixels greater than 2.0 standard deviations from the mean are shown in gray. Zoomed box is the primarily agricultural region of Brčko.

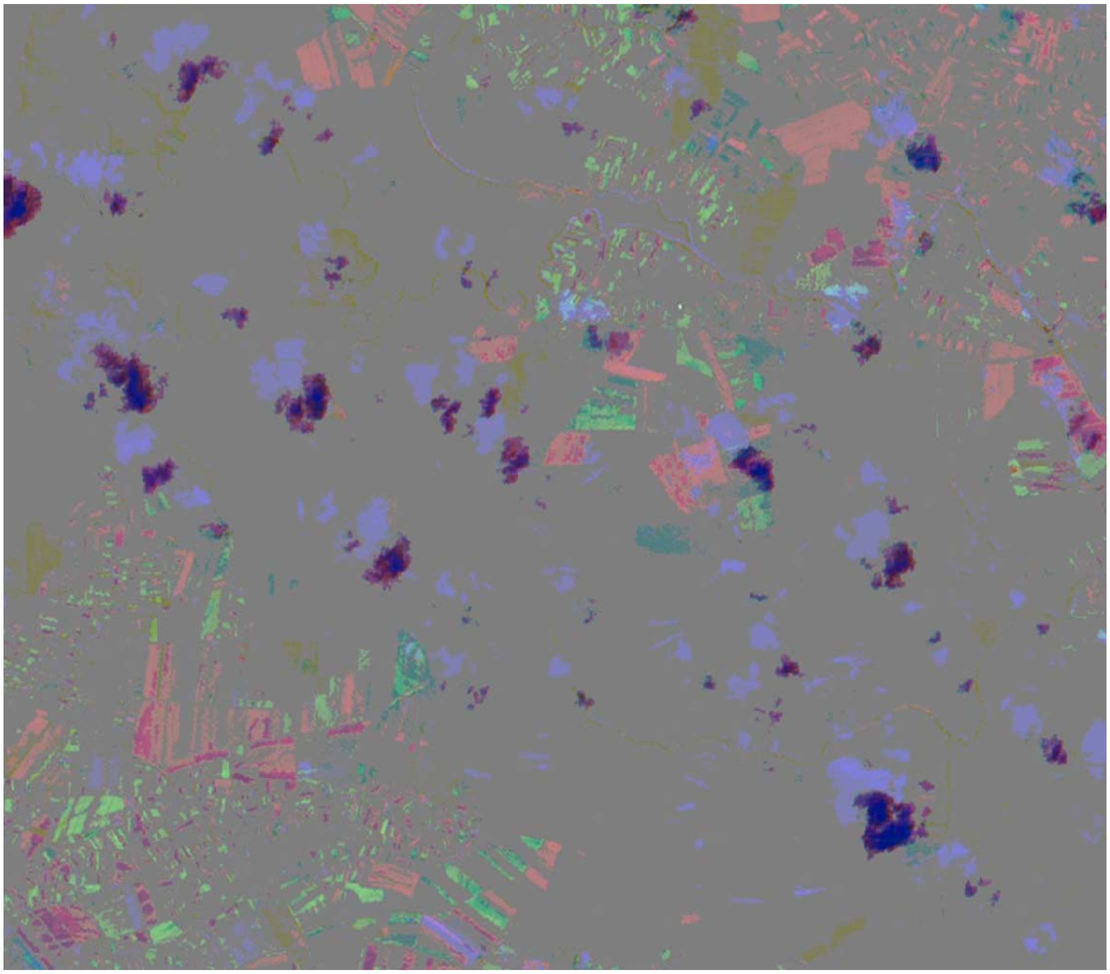

**Figure 5.** MAD change detection results for bands 3-5 of June 1991 and May 2005, east scenes. A subset of the scene is displayed here in the MAD Viewer for the area northeast of Brčko with clouds (dark purple), cloud shadows (light blue), and active agricultural land (pink and green depending on when the field was plowed/harvested) clearly visible as areas of significant change.

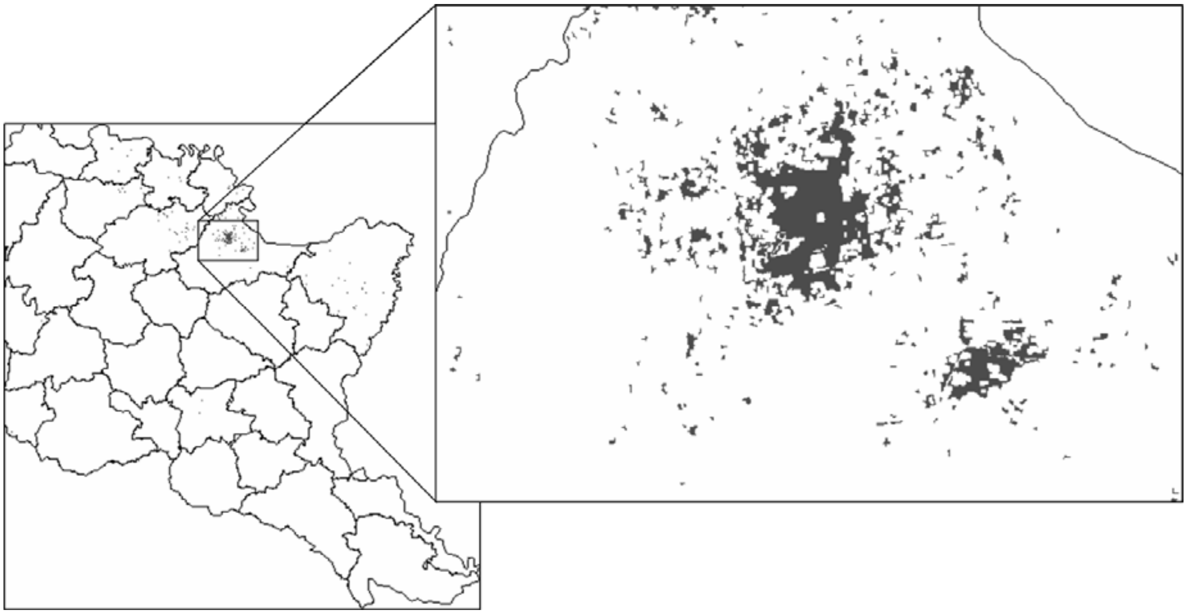

**Figure 6.** Four minimum distance supervised classifications combined for the east scenes of the study area using all six scenes from 1991, 1994, 2000, and 2005. Pixels classified as abandoned agricultural land are shown in gray. The zoomed box is the primarily agricultural region of Brčko with the large area of known abandoned land clearly visible.

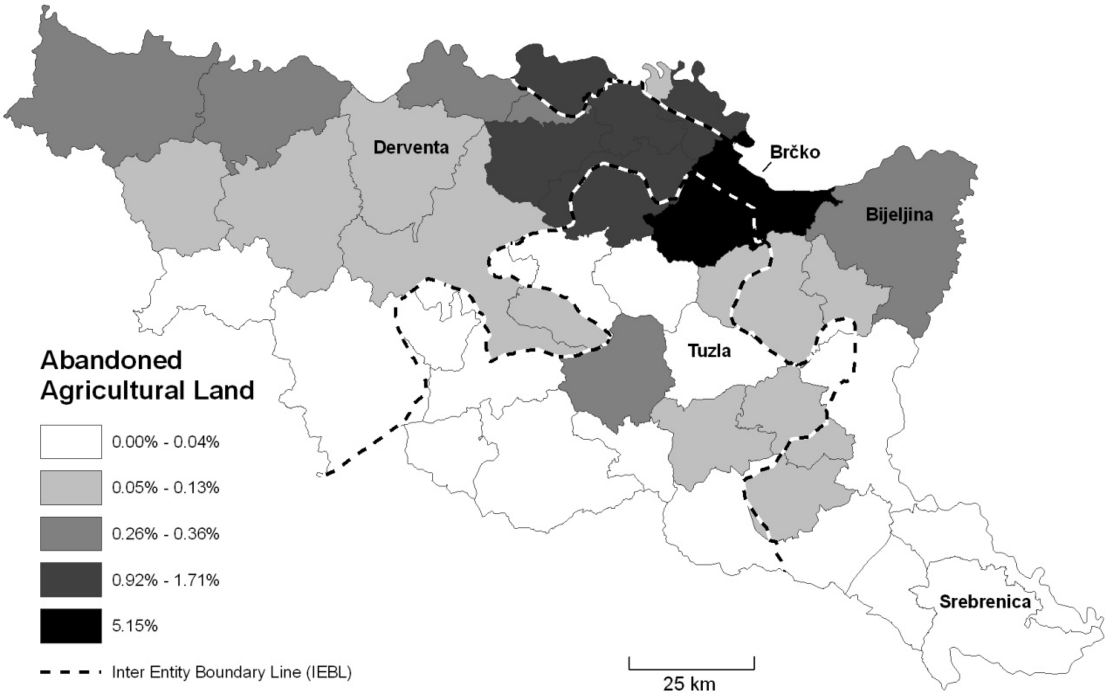

**Figure 7.** Percentage of total agricultural land classified as abandoned from the supervised classification method. Key *opstini* selectively labeled.

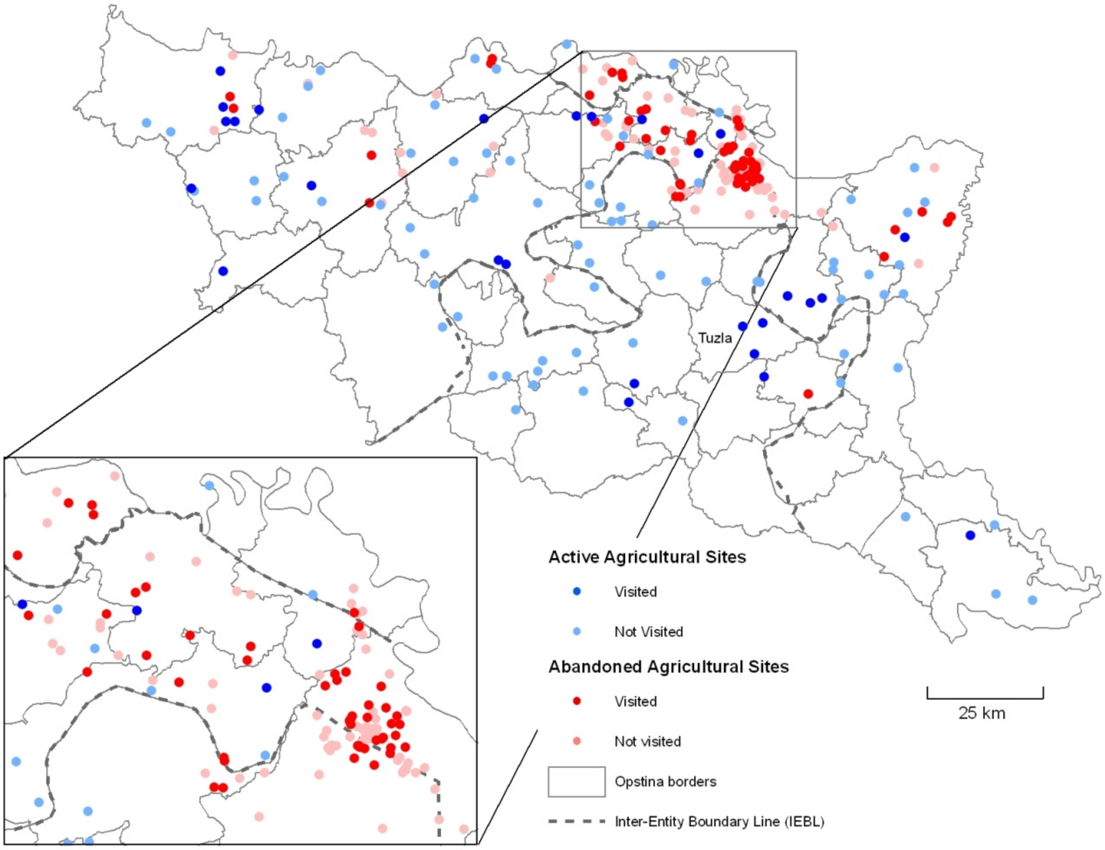

**Figure 8.** Location of sampled ground reference sites for accuracy assessment.

**Figure 9.** Example of mixed land use, small agricultural plots interspersed with forest. Photo taken 28 May 2006 near Doboj.

**Figure 10.** Example of abandoned agricultural land, a combination of weeds, bushes, and small trees. Photo taken 26 May 2006 in the Brčko district.