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BULC-U: Sharpening Resolution and Improving Accuracy of Land-Use/Land-Cover Classifications in Google Earth Engine

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Received: 30 June 2018; Accepted: 6 September 2018; Published: 12 September 2018

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Abstract: Remote sensing is undergoing a fundamental paradigm shift, in which approaches interpreting one or two images are giving way to a wide array of data-rich applications. These include assessing global forest loss, tracking water resources across Earth's surface, determining disturbance frequency across decades, and many more. These advances have been greatly facilitated by Google Earth Engine, which provides both image access and a platform for advanced analysis techniques. Within the realm of land-use/land-cover (LULC) classifications, Earth Engine provides the ability to create new classifications and to access major existing data sets that have already been created, particularly at global extents. By overlaying global LULC classifications—the 300-m GlobCover 2009 LULC data set for example—with sharper images like those from Landsat, one can see the promise and limits of these global data sets and platforms to fuse them. Despite the promise in a global classification covering all of the terrestrial surface, GlobCover 2009 may be too coarse for some applications. We asked whether the LULC labeling provided by GlobCover 2009 could be combined with the spatial granularity of the Landsat platform to produce a hybrid classification having the best features of both resources with high accuracy. Here we apply an improvement of the Bayesian Updating of Land Cover (BULC) algorithm that fused unsupervised Landsat classifications to GlobCover 2009, sharpening the result from a 300-m to a 30-m classification. Working with four clear categories in Mato Grosso, Brazil, we refined the resolution of the LULC classification by an order of magnitude while improving the overall accuracy from 69.1 to 97.5%. This "BULC-U" mode, because it uses unsupervised classifications as inputs, demands less region-specific knowledge from analysts and may be significantly easier for non-specialists to use. This technique can provide new information to land managers and others interested in highly accurate classifications at finer scales.

Keywords: land cover; deforestation; Brazilian Amazon; Bayesian statistics; BULC-U; Mato Grosso; spatial resolution; Landsat; GlobCover

1. Introduction

Land use and land cover (LULC) change is a principal contributor to global greenhouse gas emissions and can have extensive indirect effects including biodiversity loss and regional hydrologic change [1–3]. Increasing global demands for agricultural commodities and other forest resources are expected to continue to put pressure on remaining forests [2,4,5]. Monitoring LULC change is critical in identifying priority conservation and restoration areas [6] and helping nations achieve their national carbon emissions targets [7,8]. LULC change in the tropics often occurs at small scales and as a result, an accurate accounting of LULC types requires data at correspondingly fine scales.

With the opening of the Landsat satellite archive a decade ago [9], a new era in remote sensing began, characterized by free data and the rapid development of time-series analysis algorithms for tracking LULC change [10–14]. There are now many potential satellite-based imagery sources spanning across more than 4 decades [9,12]. While Landsat represents the longest-running time series, additional sensors also provide free imagery [15,16]. More recently, Sentinel-2 satellites were launched in 2015 and 2017 with even finer spatial resolution and revisit times [17,18]. The increase in data at fine resolutions and in time increases the potential benefit of algorithms to incorporate evidence from large numbers of satellite images into useful maps for monitoring landscape changes.

An earlier generation of global LULC classifications was developed by both academic and governmental organizations to represent LULC at a static point in time. Some examples include: The IGBP-DISCOVER classification using MODIS imagery [19]; the Global 1-km Consensus Land-cover Product [20]; and GlobCover, using data from MERIS in two different campaigns: 2000 and 2009 [21–23]. Made and verified with great effort, these classifications are a valuable source of LULC information that have been applied for identifying patterns of land use change [24–26], agriculture inventory [27,28], and modeling species distribution [29–31]. Despite the power of these classifications, the relatively coarse spatial resolution can limit their usefulness, especially at finer scales [28,32,33]. Surprisingly few algorithms are available to sharpen the spatial resolution of moderate-resolution LULC classifications in light of finer-scale imagery.

The Bayesian Updating of Land Cover (BULC) algorithm [34] was originally devised to use Bayesian logic to create time series of land use and land cover classifications. In its original conception, BULC processes classifications to estimate the probability for each class for each pixel at each time step based on the strength of the agreement between consecutive candidate classifications. This approach allows each pixel to incorporate information from a series of land cover maps to create ongoing classifications, either to update a given classification through time or to confirm the estimated LULC class of each pixel in a study area at a given time. The effect is to blend relative candidate classifications according to their shared properties, while tracking stability and change through time as more images are analyzed. A given pixel's per-class probabilities reflect the ability to consistently label a pixel with its (assumed proper) class. Despite its utility for creating time series, initial applications of BULC were limited by the effort and foreknowledge needed to produce relatively high-quality LULC classifications across a large number of images: prospective users need to know the study area well enough to discern whether a given prospective classification is good enough for inclusion based on the identified LULC categories.

In this manuscript, we modify BULC's ability to incorporate new information by extending its potential inputs to include unsupervised classifications. We use this enhancement, which we call "Bayesian Updating of Land Cover: Unsupervised" (BULC-U) to refine the resolution of a relatively coarse global data set by an order of magnitude in a heterogeneous, finely structured landscape in Mato Grosso, Brazil. Using 13 Landsat 5 images near in time to the nominal 2009 date of the GlobCover global data set, BULC-U blends Landsat's finer-scale spatial information with the coarse labels of GlobCover 2009 to produce a higher-resolution land-cover classification with GlobCover 2009's labels and Landsat 5's spatial resolution. We conduct an accuracy assessment comparing the GlobCover 2009 and the BULC-U 2009 classification products, demonstrating that the new classification has both finer spatial resolution and improved accuracy.

2. Methods

2.1. Study Area

The study area is a 2×10^5 km^2 (166 km $\times$ 121 km) region of Mato Grosso, Brazil, located within Landsat path 224 row 69 and centered near 51.884°W, 12.601°S. (Figure 1).

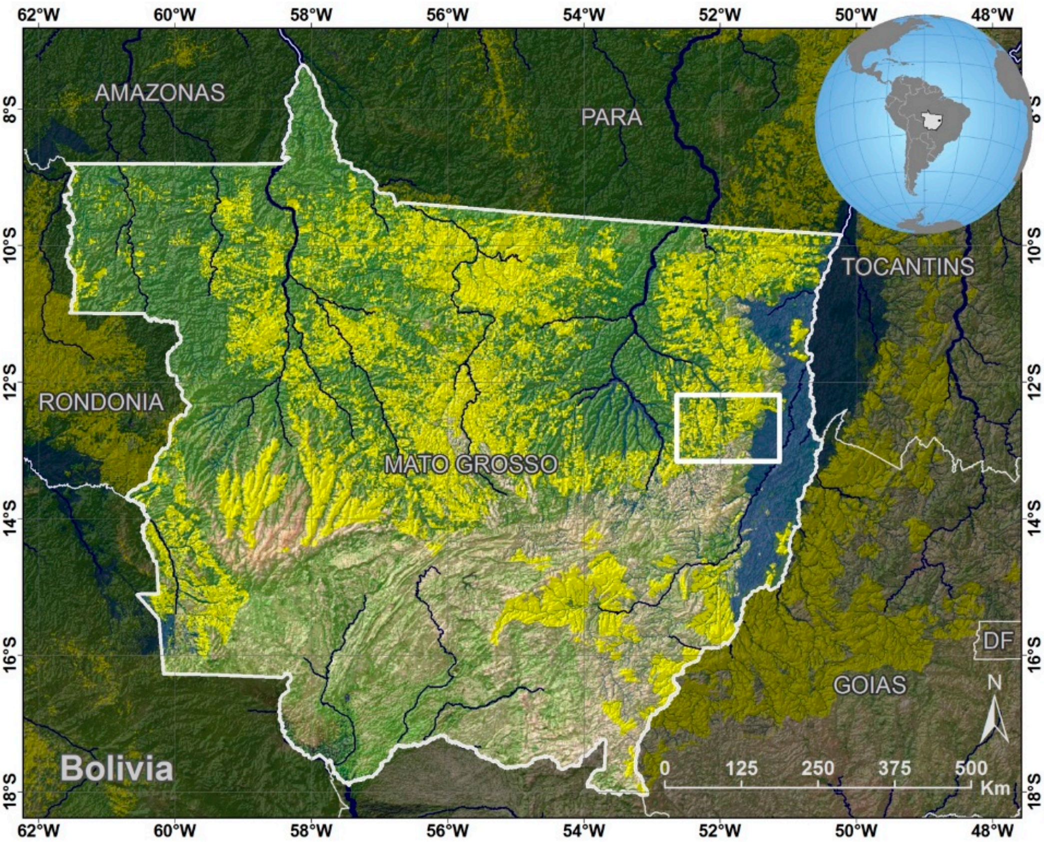

Figure 1. Location of study area in eastern Mato Grosso, Brazil.

The study area has a mix of grasslands, rainforest, hilly shrubland and extensive agricultural areas. The varied land cover types and clearly visible agriculture make this area a good location for testing the ability of BULC-U to sharpen a coarser classification. In particular, 30-m satellite imagery shows well-demarcated edges between cropland and forest that are difficult to capture with 300-m resolution imagery. In addition, the small rivers that run through the area, visible in 30-m imagery, are not discernible at coarser scales.

2.2. LULC Categories

For this study, we were interested in illustrating the study area during its conversion from a landscape that had recently been mostly dense-canopy Forest or some type of Grassland or Shrubland to one increasingly dominated by Cropland. We identified four fundamental LULC categories of interest: Cropland; Forest; Shrubland or Grassland (referred to hereafter as Shrubland); and Water. These four classes are easy to visually identify in this area in Landsat-scale satellite images, and are useful in this study for detecting active agriculture that may be missed in coarsely grained classifications.

2.3. BULC-U Algorithm

BULC-U is intended to track classes that can be reliably identified in a sequence of images that have been categorized into Events. The BULC-U algorithm can sharpen an existing LULC classification by incorporating higher-resolution information from unsupervised classifications of finer-resolution satellite images. Like the BULC algorithm on which it is based, BULC-U ingests a time-ordered series of classified images and creates a land cover classification at each time step (Figure 2).

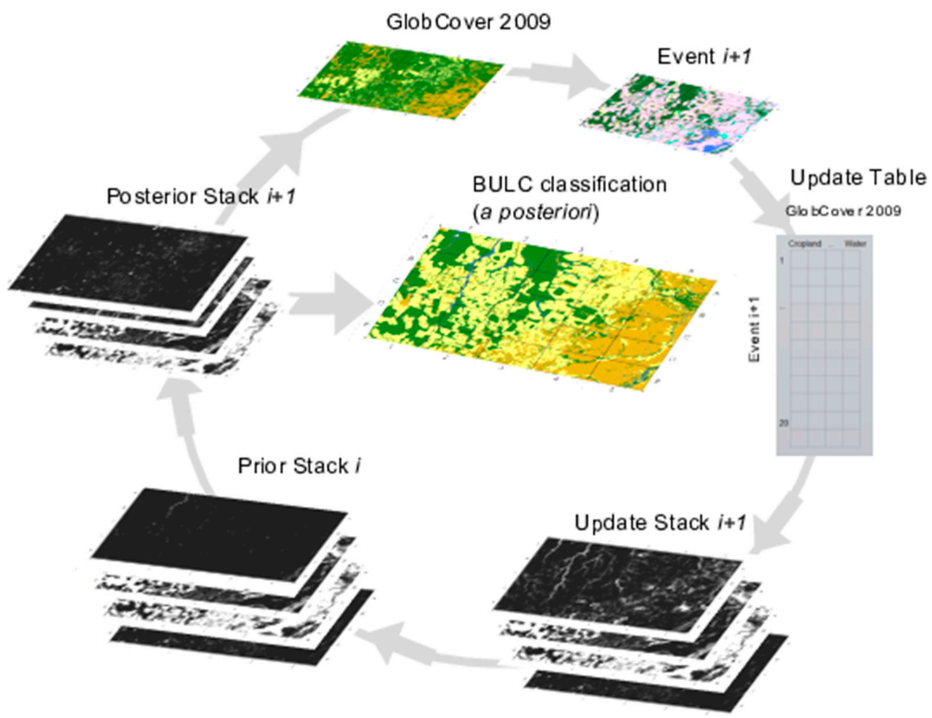

Figure 2. Schematic of BULC-U. The BULC-U processing is driven by unsupervised classifications and update tables relating them to a common reference classification (here, the GlobCover 2009 classification). As in BULC, evidence from each new Event is used to update the estimates of each pixel's LULC using Bayes' Theorem.

At each time step, BULC-U tracks an estimate of the probability of each land cover class for each pixel. Like BULC, BULC-U initializes the land cover estimate using a reference classification that represents the best existing estimate of LULC in the study area. The series of classified images, which we term 'Events', is created using unsupervised classification algorithms. BULC-U creates an 'update table' (formed like an accuracy assessment table) to compare the evidence from the Events to the reference classification following the methods outlined in Cardille and Fortin [34]. In this application, the reference classification was the 300-m GlobCover 2009 classification and Events were made from 30-m Landsat images, both prepared as described in the subsections immediately below. The BULC-U process begins with the *a priori* proposition that the LULC in the study area is exactly as seen in the reference classification, with a moderate level of confidence. The evidence from an Event is combined with the *a priori* estimate using Bayes' Theorem to create an *a posteriori* vector of probabilities for each pixel, which is used as the new *a priori* estimate for incorporating evidence from the next Event. The highest probability class of each pixel in the *a posteriori* stack can be assessed to create a BULC-U classification at any time step in every location given the information that has been seen to that point in the process. BULC and BULC-U differ in two small but important ways. The first difference is in the nature and shape of the update table—where the BULC table is square (n $\times$ n for n tracked classes), the update table in BULC-U is m $\times$ n, where m is the number of classes in the unsupervised classification for an Event. The two methods also differ in the classification used as the nominal 'reference' classification in making the update table: In BULC-U, the update table is made for an Event by cross-tabulating the Event with the reference classification, not another Event as is done in BULC.

Another very substantial difference between BULC and BULC-U is its implementation in Google Earth Engine [35]. BULC was implemented as experimental code in R and could take up to several days for a run, making troubleshooting difficult and severely limiting the number of images that could be processed, the amount of data that could be retained at each time step, and the area that could be analyzed. BULC-U was implemented in Google Earth Engine's JavaScript platform, which permits easy prototyping, parameter exploration, and interactive visualization. It is also much faster: The same BULC logic of Cardille and Fortin [34], running in Earth Engine, takes a few moments for its calculations. The BULC and BULC-U methodology also take advantage of a sequential iterator tool that distinguishes it from most other work in Earth Engine. In contrast to studies that use Earth Engine's power to compute, say, the maximum greenness value for a year, BULC and BULC-U process an Event, update the state of each pixel, then process another Event, for a known finite set of Events. The iteration of BULC-U through a series of events is described below.

In this context, BULC-U operates as follows: At the beginning of a given iteration *i* of BULC-U, each pixel has an estimated probability vector for each LULC category, which reflects the evidence seen to that point in the process about LULC in that pixel. An update table is formed for Event *i* (an unsupervised Landsat classification) by cross-tabulation with the reference GlobCover classification. This table quantifies the extent to which each unsupervised class coincides with one of the LULC categories. If, say, class 7 of Event *i* very strongly coincides with Agriculture pixels in the GlobCover classification, the probability vectors of class 7 pixels change in the direction of Agriculture. Each pixel maintains its own history as described in Cardille and Fortin [34]. In the next iteration, a new Event $i + 1$ is considered—say, with class 11 of Event $i + 1$ coinciding with Agriculture pixels in the GlobCover classification, though not as strongly as class 7 had in iteration *i*. When updated, the probability vectors of those class 7 pixels would move again toward Agriculture, though not as strongly as class 11 pixels had in iteration *i*. Pixels that were in class 7 in Event *i* and class 11 in Event $i + 1$ would have moved considerably toward agriculture; pixels in class 7 in *i* and then a different class in $i + 1$ would have a different probability vector that reflected their own history. The preparation of the Events and the reference classification are described below.

2.4. GlobCover 2009

GlobCover is a global LULC classification with 300-m resolution and 22 potential categories, created with a nominal date of 2009 using data from the MERIS sensor [23]. Within the study area, the GlobCover 2009 LULC classification had 14 categories. Of these, seven covered more than 1% of the study area. Several of the classes were too specific for our purposes and were reclassified to one of the four categories to begin the BULC-U process. Specifically, "Rainfed Cropland (5% of the study area)" and "Mosaic Cropland" (mixed pixels strongly dominated by Cropland, 14% of the area), were reclassified as "Cropland" for the BULC-U reference layer. Second, the Forest-dominant categories "Closed to Open Broadleaved Evergreen" (33%), "Closed Broadleaved" (13%), "Flooded Broadleaved" (<1%), and "Open Broadleaved" (<0.1%) were reclassified as "Forest" for the BULC-U process. The Shrubland category was comprised of GlobCover classes "Closed to Open Shrubland" (17%), "Flooded Closed to Open Vegetation" (4%), "Closed to Open Grassland" (<0.1%), and "Sparse" (<0.1%). The "Water" LULC category was made of the "Open Water" GlobCover category. Importantly, some GlobCover categories potentially contained elements of two BULC-U target classes. These included: "Mosaic Vegetation", which comprised 13% of the study area in GlobCover; "Mosaic Forest or Shrubland" (1% of the study area), and a few pixels of "Mosaic Grassland". These were initialized as "Mosaic/Unknown" for the purposes of creating BULC-U's *a priori* classification. The effect was for BULC-U to not use spectral information of those classes to refine GlobCover. Rather, they were treated as areas whose LULC was not known clearly before the study, to be filled in with one of the four tracked LULC categories at the 30-m resolution during the BULC-U refinement process. The effect of the remapping was to condense original GlobCover categories into a set of LULC categories that could be reliably distinguished on Landsat imagery, and that were known to be accurate in the GlobCover validation report [23].

As it met our purposes of tracking the development of cropland in the area, there were indications that GlobCover was properly used only for these Level 1 categories within our study area. The GlobCover validation report [23] (which assessed points worldwide) considered the two cropland classes within our study area to be interchangeable for judging user's accuracy. Meanwhile, significant confusion was noted in the GlobCover report between the classes of evergreen broadleaf forest and closed deciduous forest, the two Level 2 forest categories that dominated forest in our study area. For shrubland, the two categories that comprised the shrubland found in our study area had user's accuracy of 50% and 20%, with the smaller of the two noted in the report for its "classification instability". Perhaps more importantly, it would have been unfair to ask the GlobCover data, a global coverage, to capture LULC to such a fine degree in an area quite small compared to its global reach. Fortunately, the desired Level 1-analogous LULC labels of our study were of sufficient quality to be used in BULC-U, as described below.

The remapped GlobCover was used in two important ways in the fusion process. First, it was used as the *a priori* classification of the area for the 86% of the study area estimated to be in one of the four tracked LULC categories. For the 14% of the pixels labeled in this way as "Mosaic/Unknown", BULC-U began with equal *a priori* probabilities and gradually refined the estimate of the LULC based on evidence from the Events as describe above. Second, the remapped GlobCover layer was used as the reference classification for the update tables. The Events with which it was compared are described below.

2.5. Landsat Imagery

Thirteen Events for BULC-U were created from clear Landsat 5 images (<10% cloud cover) spanning 2008 to 2010 (Table 1). BULC-U uses unsupervised classifications as its Events, meaning that the multidimensional color space of Landsat needed to be reduced into groupings with similar spectral characteristics. Exploratory efforts to classify images revealed considerable speckling that was not greatly improved with smoothing techniques. Since the distinctive edges of agricultural fields are often amenable to image segmentation methods [36], we segmented the images. Unsupervised classification techniques were unavailable in Google Earth Engine, and so we downloaded the images into ArcGIS for analysis. Each Landsat 5 image was segmented using the ArcGIS implementation of the Segmented Mean Shift algorithm (ESRI 2014) using bands 4, 5, and 7, which were clear and informative for segmenting the images. The segments of each unsupervised classification were then classified using the well-known ISODATA unsupervised classification tool [37,38] in ArcGIS with 20 unsupervised classes. Each of the resulting Events represented groups of pixels that mostly followed apparent LULC distinctions in the landscape, with much of the speckling removed during the segmentation (Figure 3). The degree to which a given unsupervised class was entirely within a single GlobCover LULC class varied among unsupervised classes and across the landscape. Determining the amount and meaning of this overlap was the work of the BULC-U algorithm. Events were then introduced in time order to the BULC-U algorithm's implementation in Earth Engine.

Table 1. Dates of Landsat images classified as Events in BULC-U.

Year	Day
2008	1 June 3 July 19 July 4 August
2009	18 June 4 July 20 July 5 August 22 September
2010	17 May 2 June 20 July 6 September

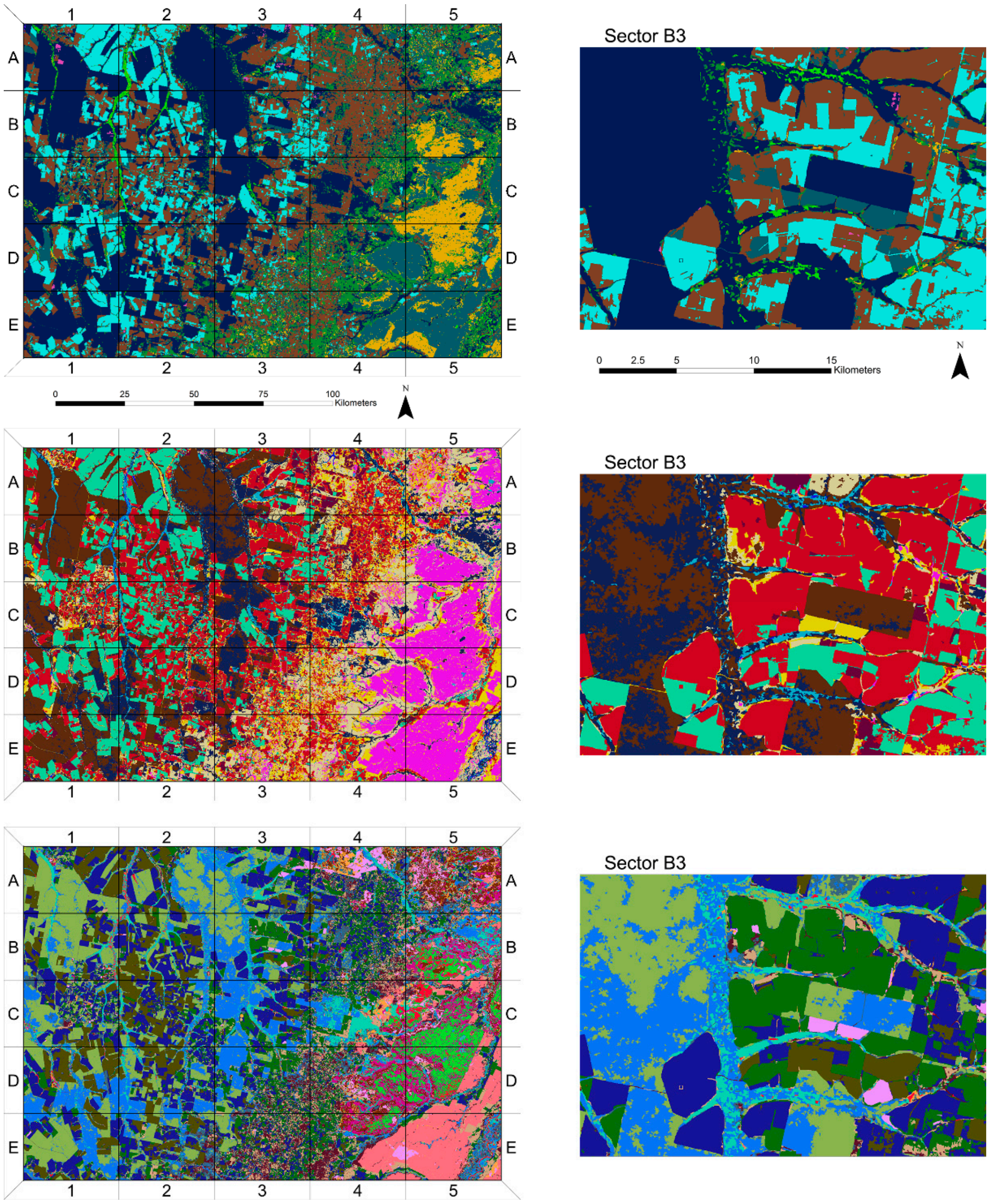

Figure 3. Three views of the study area on three different dates (18 June 2009, 5 August 2009, and 22 September 2009), as shown in the unsupervised Landsat classifications used as Events by BULC-U to refine the GlobCover 2009 classification. Left panel shows the complete study area with a reference grid superimposed; right panels show sector B3 of each classification. To create Events, each Landsat image was first segmented into relatively homogeneous regions. The band means of these regions were then clustered with unsupervised classification into 20 categories for processing as Events in BULC-U. The classifications are similar in that they are mostly successful in distinguishing LULC categories, such as Forest and Agriculture, from each other. As described in the text, BULC-U uses the degree and nature of the correspondence between GlobCover 2009 and each of these unsupervised classes to inform the probability that each of these classes is each of the tracked LULC categories. Based on this correspondence, BULC-U updates the probabilities of each class for each Landsat-sized pixel as each Event is introduced into BULC-U.

2.6. Validation

Validation of the GlobCover and BULC-U classification was done by a researcher unassociated with this project, with experience classifying time series in Mato Grosso and accuracy assessment. The simple LULC classification categories enabled straightforward comparison of the GlobCover and BULC-U classifications while avoiding complex ontological questions about the specific meaning of similar LULC types, and without being needlessly demanding of labeling accuracy in a 300-m classification. We validated both GlobCover 2009 and BULC-U 2009 with the same protocol and classes. The assessment was made by determining land cover from visual inspection of a clear Landsat 5 image that was not used in the BULC-U process. The image was from 12 September 2010 and is shown at various scales in Figure 4 and later. We identified 400 points across the study area, using 100 points each for the Cropland, Forest, Shrubland and Water. To identify reference points for the Cropland, Forest, and Shrubland classes, several thousand candidate reference points were first generated at random locations across the study area using the Create Random Points tool in ArcGIS. Points were viewed on the Landsat validation image and evaluated as being a member of one of the three terrestrial classes; any points within 30 m of an edge of two LULC classes were discarded and the next random point considered, until 100 points were found for each of the three terrestrial categories. Points that appeared in locations that had been labeled as Mosaic/Unknown when preparing the reference classification were discarded. Reference points for Water, which was a much rarer LULC class, were identified using the mask of permanent water bodies from Hansen et al. [39]. We generated a large number of candidate points randomly (again with the Create Random Points tool in ArcGIS) located within that data set's Water mask, retaining the first 100 that were identifiable as open water on the reference Landsat image and more than 30 m from an edge of two LULC categories. A confusion matrix was then created between the 400 reference points and both the GlobCover 2009 classification and the BULC-U classification to determine standard assessment values of Overall Accuracy, Producer's Accuracy, and User's Accuracy [40].

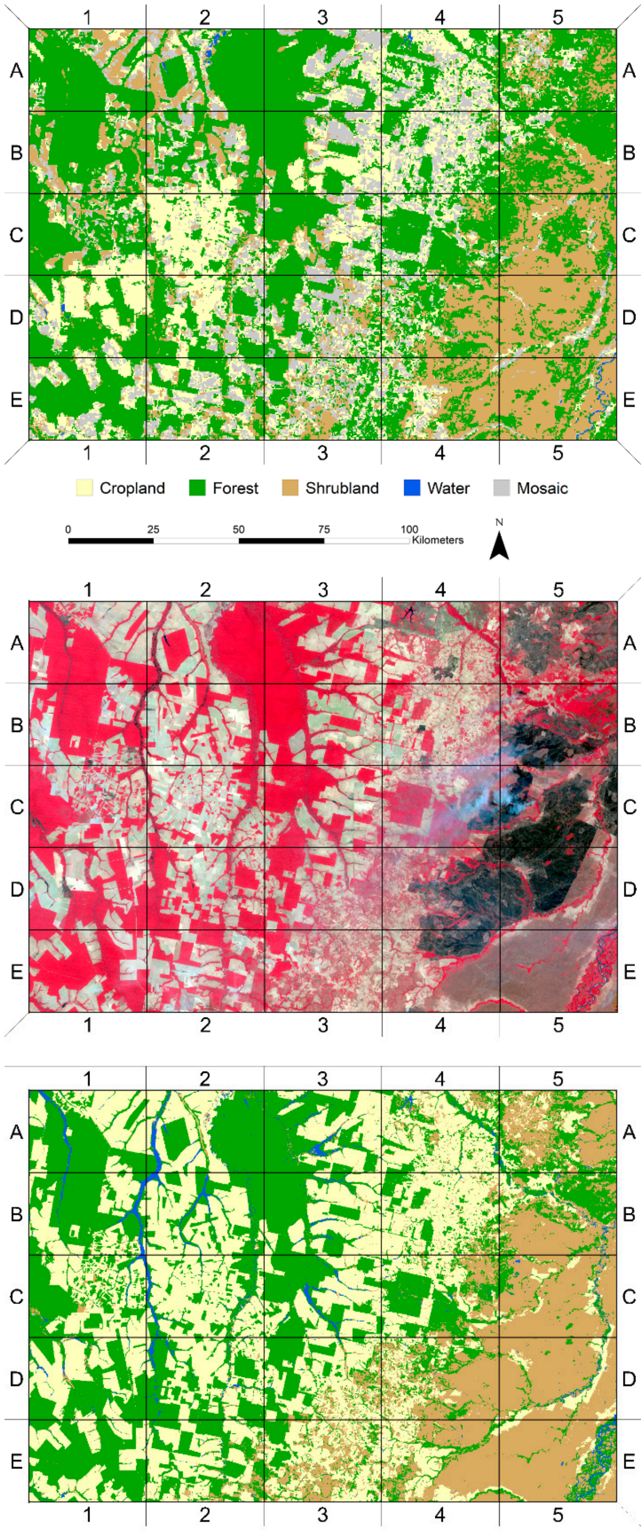

Figure 4. Comparison of GlobCover 2009 (**top**), Landsat 5 (**middle**) and BULC-U 2009 (**bottom**), showing the coarse resolution of GlobCover, the increased level of spatial detail available with Landsat, and the resulting BULC-U 2009 image created by fusing Landsat imagery and GlobCover 2009. The Landsat image is from 12 September 2010.

3. Results

Compared to the GlobCover 2009 300-m classification on which it was based, the resulting BULC-U 2009 classification represents LULC in the year 2009 (Figure 4) with a finer spatial resolution and considerably greater accuracy in all four validation categories (Table 2).

Table 2. Accuracy assessments of GlobCover and BULC-U 2009.

Land Cover Classification Accuracy				
		GlobCover	**BULC-U 2009**	**Improvement**
	Overall	69.1%	97.5%	28.4%
Producer's	Agriculture	71.0%	99.0%	28.0%
	Forest	98.0%	98.0%	0.0%
	Shrubland	67.0%	93.0%	26.0%
	Water	40.8%	100.0%	59.2%
User's	Agriculture	83.1%	95.2%	12.1%
	Forest	59.5%	98.0%	38.5%
	Shrubland	64.4%	97.9%	33.5%
	Water	100.0%	99.0%	-1.0%

The Overall Accuracy of the BULC-U 2009 classification (97.5%) is substantially higher than that of the GlobCover 2009 classification (69.1%) in the study area (Table 2). Within individual classes, the Producer's Accuracy values of BULC-U 2009 were substantially higher than that of GlobCover 2009 for three of the LULC categories: 28.0% higher for Cropland, 26.0% higher for Shrubland, 59.2% higher for Water.

Producer's Accuracy of the Forest category was equally high (98%) in both classifications. User's Accuracy values of BULC-U 2009 were also high for each class in the BULC-U 2009 classification, with all four accuracies above 95%. Meanwhile, through the incorporation of classifications based on 30-m imagery, the resulting BULC-U 2009 classification resolution appears as spatially refined as the Landsat data itself, creating a classification sharpened by a factor of 10 when compared to GlobCover.

From its initialization as the GlobCover classification, the introduction of Events changed the intermediate BULC-U classifications greatly over the first iterations and stabilized after ingesting several unsupervised classifications (Figure 5). The progression from the GlobCover *a priori* map to the BULC-U classification can be seen in Figure 6 and, in a closer view, in Figure 7, as well as the Video Abstract. GlobCover's fusion with the information from Landsat can be directly seen in those figures as the eye moves from the GlobCover panel, to Iteration 1, then Iteration 2. The GlobCover panel (Figures 6 and 7, upper left) is the best estimate of the area before any new data is considered. Figures 6 and 7's Iteration 1 panel is the best estimate by BULC-U of the area after the GlobCover classification was fused with the first Event via BULC-U. Iteration 2 shows an intermediate product that is a fused set based on GlobCover, Event 1, and Event 2. It mostly "looks like" the GlobCover classification, but is in the process of sharpening the classification in light of both the GlobCover reference and the Events—for example, reclassifying some of the pixels that will be eventually be called Water in the finer-scale BULC-U classification after all Events have been processed.

The convergence of the process suggests a spin up time of about 6 Events, with minimal differences thereafter. The convergence was evident both for the proportions (Figure 5) and, importantly, of the maps themselves between iterations (Figure 6). In observation of the LULC maps at both large (Figure 6) and much smaller (Figure 7) extents, later iterations were only slightly different from each other, with fewer than 1% of the pixels changing between iterations after BULC-U had ingested several Events.

Although the BULC-U and GlobCover 2009 classifications appear at first view to be quite similar, BULC-U revealed that the GlobCover map substantially overestimated the amount of Forest and under-reported Cropland in its assessment of the land use and land cover of the area (Table 3).

Before the BULC-U refinement process began, 45.7% of the study area was estimated as Forest by GlobCover, even without including the Forest implied by the Mosaic categories that we had recategorized to be an unknown LULC. This contrasts with what is indicated (35.1%) by the more accurate and finer-scale BULC-U 2009 classification, an estimate that is 23% lower. Closer inspection indicates that much of what was called Forest in the GlobCover classification was either mislabeled (as in sector B2), or, more often, labeled properly at the 300-m scale but contained substantial Cropland within. The amount of Cropland was more than double that estimated by GlobCover (40.0% vs. 19.2%). This very substantial difference is more than a distinction between LULC labels: even if all pixels in the GlobCover mosaic categories had been Cropland in truth, the BULC-U estimate of Cropland was even higher than what could be detected in the GlobCover reference set. In practice, the higher estimate of Cropland came both from better labeling of some GlobCover Forest pixels (Figures 8 and 9) and from splitting and labeling the 14% of the GlobCover 300-m classification that had been labeled as a Mosaic category (see especially Figure 9).

Table 3. Proportions of each category compared between GlobCover 2009 and derived BULC-U 2009. Note that GlobCover, a 300-m classification, had 14% of its area labeled as Mosaic classes that were relabeled as NoData for the BULC-U process. BULC-U's 30-m classification eliminated those mosaic categories in favor of their component LULC classes.

	Percentage Cover		
	GlobCover	**BULC-U 2009**	**Amount Loss/Gain**
Forest	45.7%	35.1%	−10.6%
Cropland	19.2%	40.0%	20.9%
Shrubland	20.8%	23.1%	2.3%
Water	0.2%	1.8%	1.6%
Mosaic	14.1%	0.0%	−14.1%

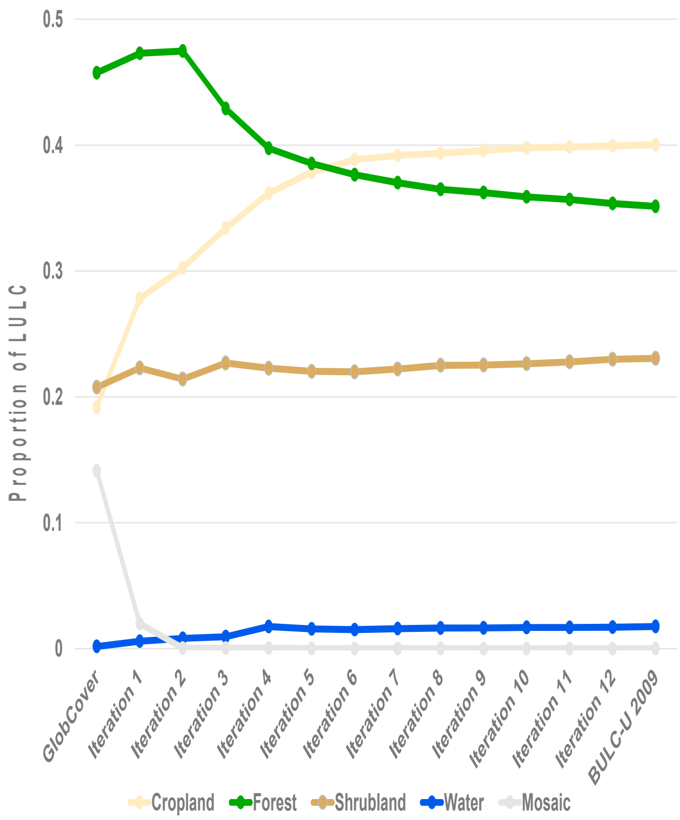

Figure 5. Convergence of the BULC-U classification across 13 iterations.

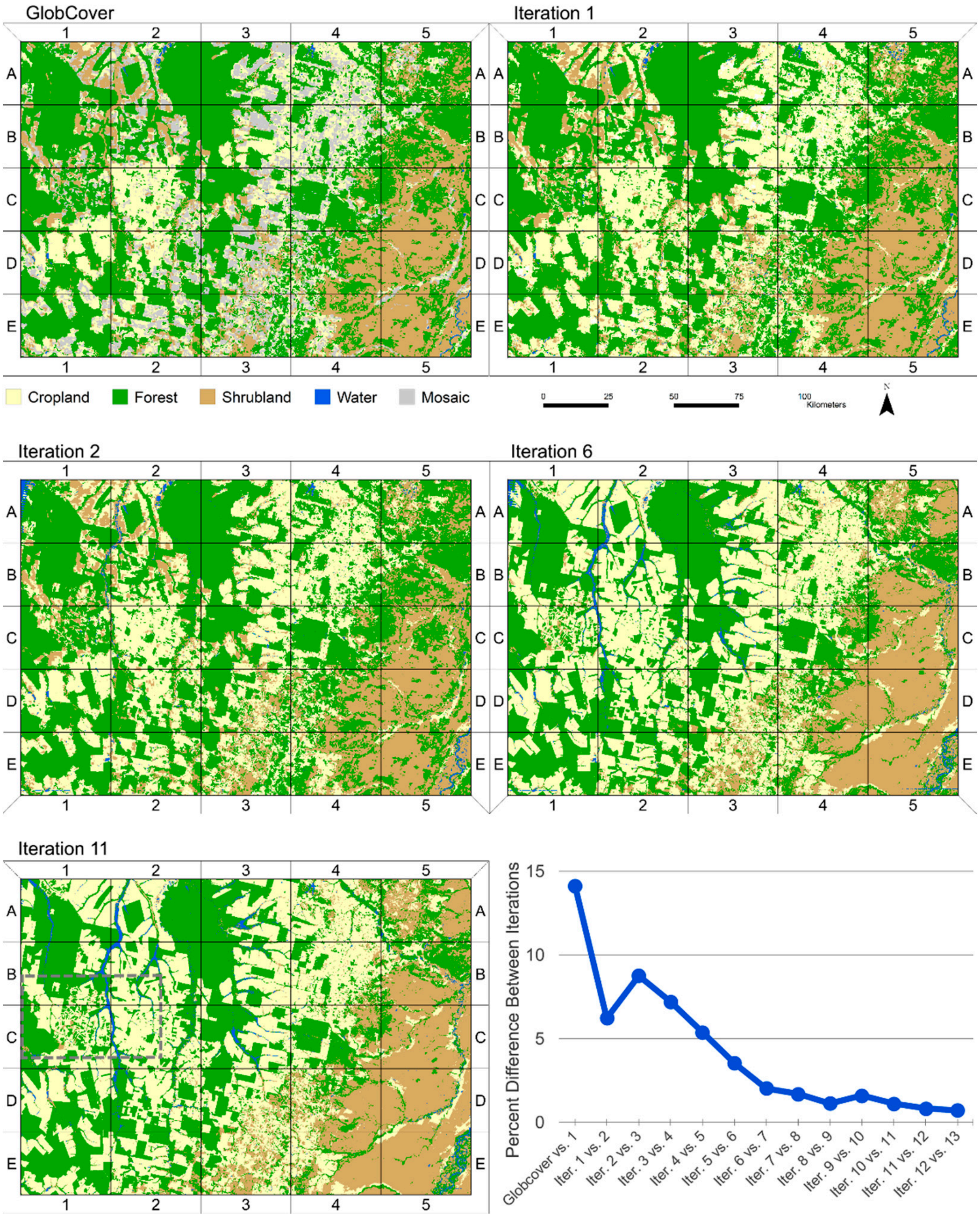

Figure 6. Progression from GlobCover 2009 LULC classification (upper left panel) toward the BULC-U 2009 classification. Shown are intermediate iterations of BULC-U as the map converges to the final classification seen in Figure 4, lower panel. Lower right panel: percentage of differing LULC labels between subsequent iterations of BULC-U, showing that iterations rapidly converge as new data is added. Fewer than 1% of pixels are different between the later iterations and the final BULC-U 2009 classification, which is taken from Iteration 13 (Figure 4, lower panel). The dashed box superimposed on Iteration 11's classifications (with the upper right corner visible on B2) is seen in Figure 7.

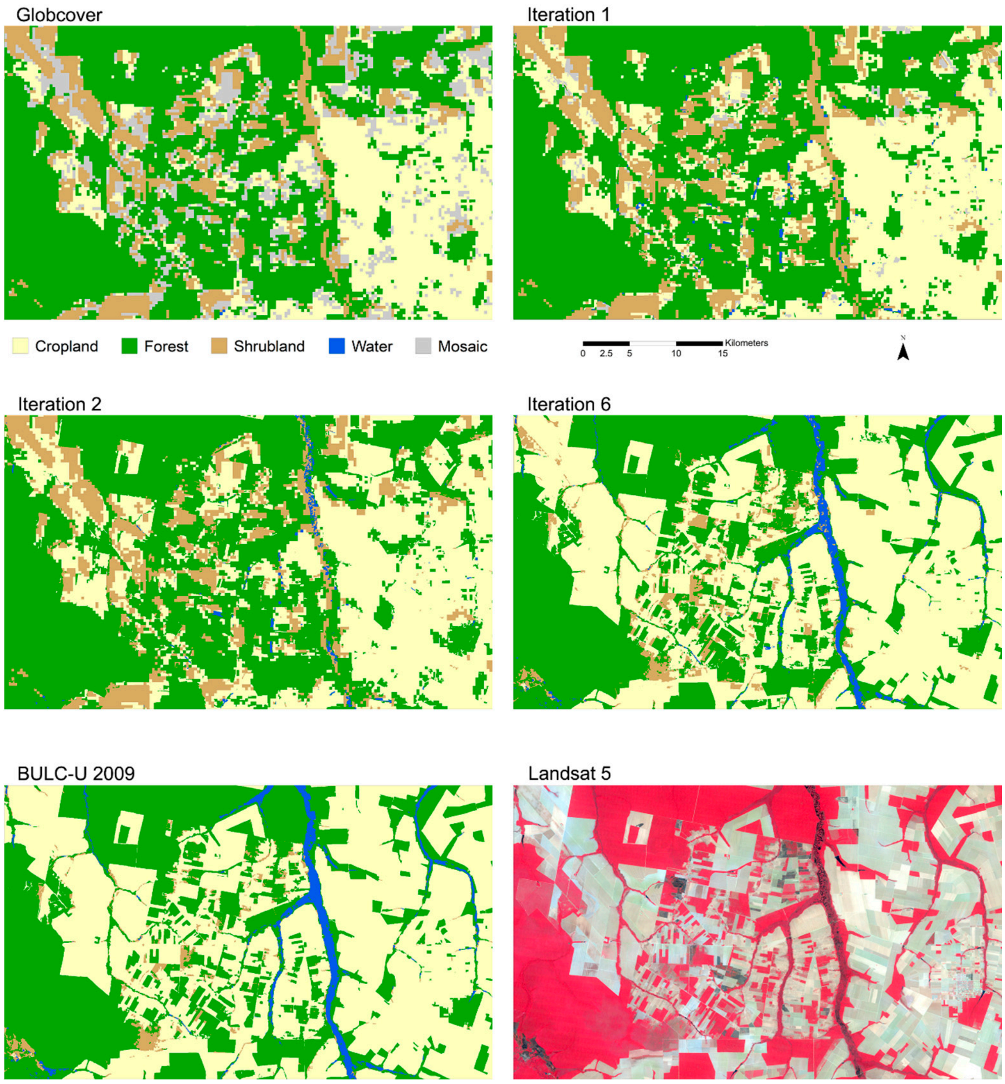

Figure 7. Progression from GlobCover 2009 LULC classification toward the BULC-U 2009 classification. The area centers on the town of Querência, whose location is shown in the dashed box on Figure 6. The BULC-U classification compares favorably with the Landsat image from 12 September 2010.

The other two categories of the BULC-U classification were also different than their counterparts in the GlobCover base image. The amount of detected open Water increased by an order of magnitude, from 0.2 to 1.8%, principally due to an increase in the number of pixels along river courses as the resolution improved with the incorporation of 30-m data. For the Shrubland category, it has roughly the same proportion in both the GlobCover and BULC-U classifications, although the location and distribution of the pixels of the class were somewhat different. This appears to have been due to the spatial configuration of Shrubland in the study area: With fewer mixed pixels than in the GlobCover 2009 Forest class, the refinement of the coarser classification tended to resolve labeling errors, rather than uncovering previously undetected pockets of Shrubland within 300-m GlobCover pixels. This can be seen most clearly in Figure 10, where the large expanse of Shrubland is mostly consistent between GlobCover and BULC-U. In most cases where Shrubland in the GlobCover category was changed by BULC-U, (e.g., in the southwest portion of Figure 8), BULC-U labeled the area Cropland. Meanwhile, some larger areas marked as Forest (e.g., in the northeast portion of Figure 10) were found by BULC-U as being more properly labeled Shrubland. These two relatively independent phenomena resulted in a Shrubland class that was more precise and accurate, with a similar amount between the two classifications (Table 3).

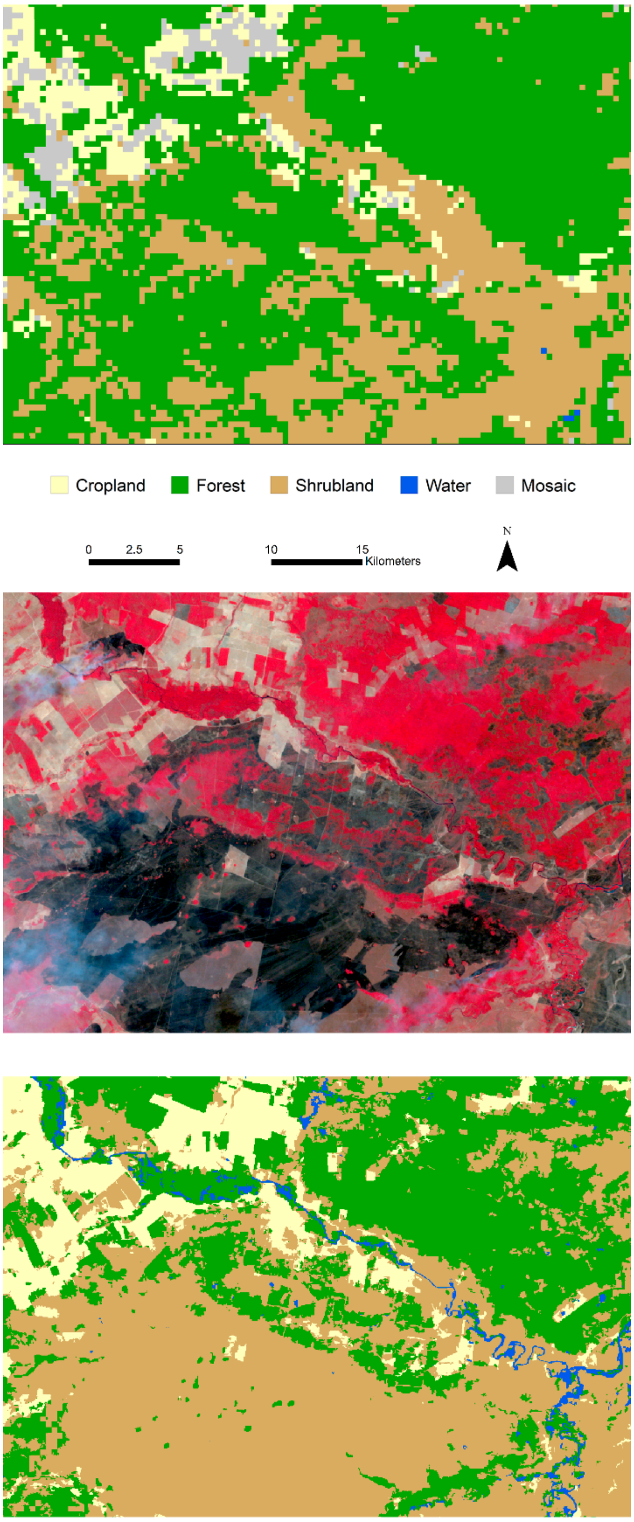

Figure 8. Closer view of Sector B5 on Figure 4, comparing GlobCover 2009 (**top**), Landsat 5 (**middle**) and BULC-U 2009 (**bottom**). The Landsat image is from 12 September 2010.

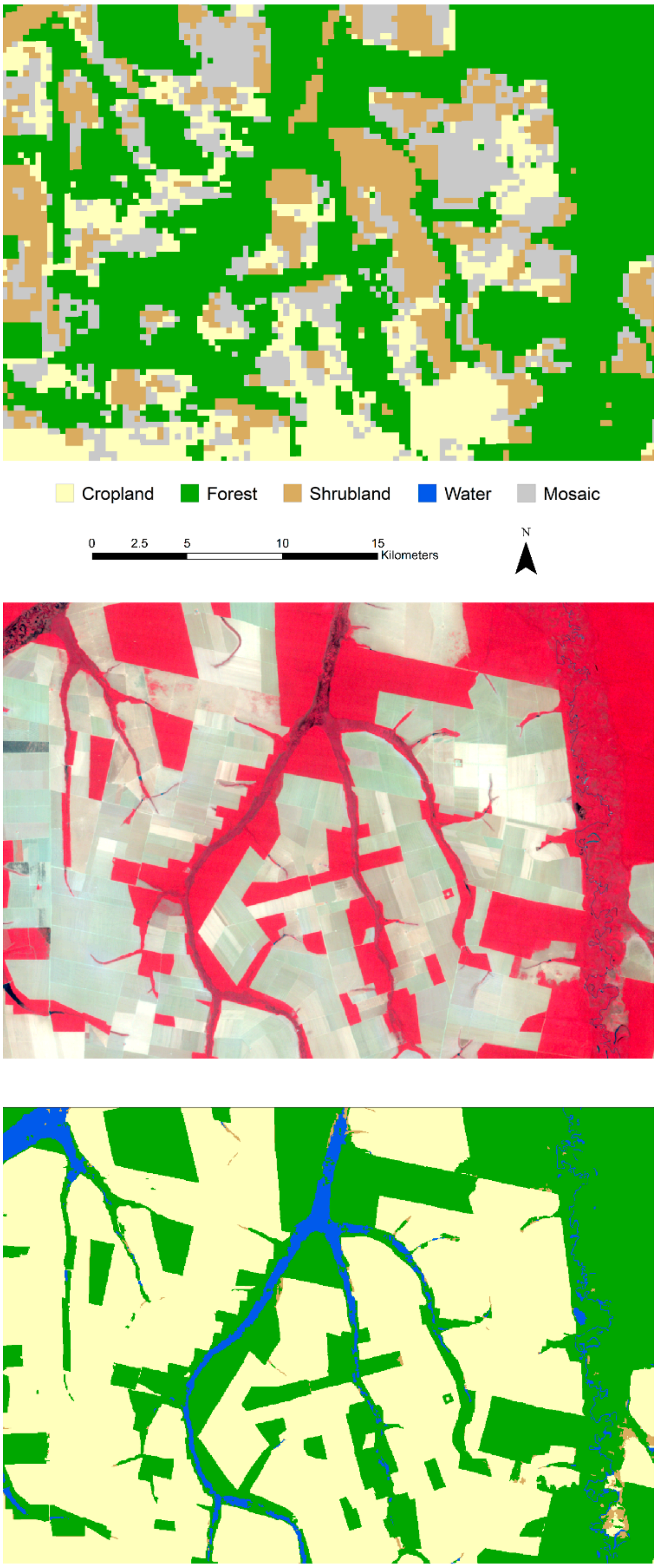

Figure 9. Closer view of Sector B2 on Figure 4, comparing GlobCover 2009 (**top**), Landsat 5 (**middle**) and BULC-U 2009 (**bottom**). The Landsat image is from 12 September 2010.

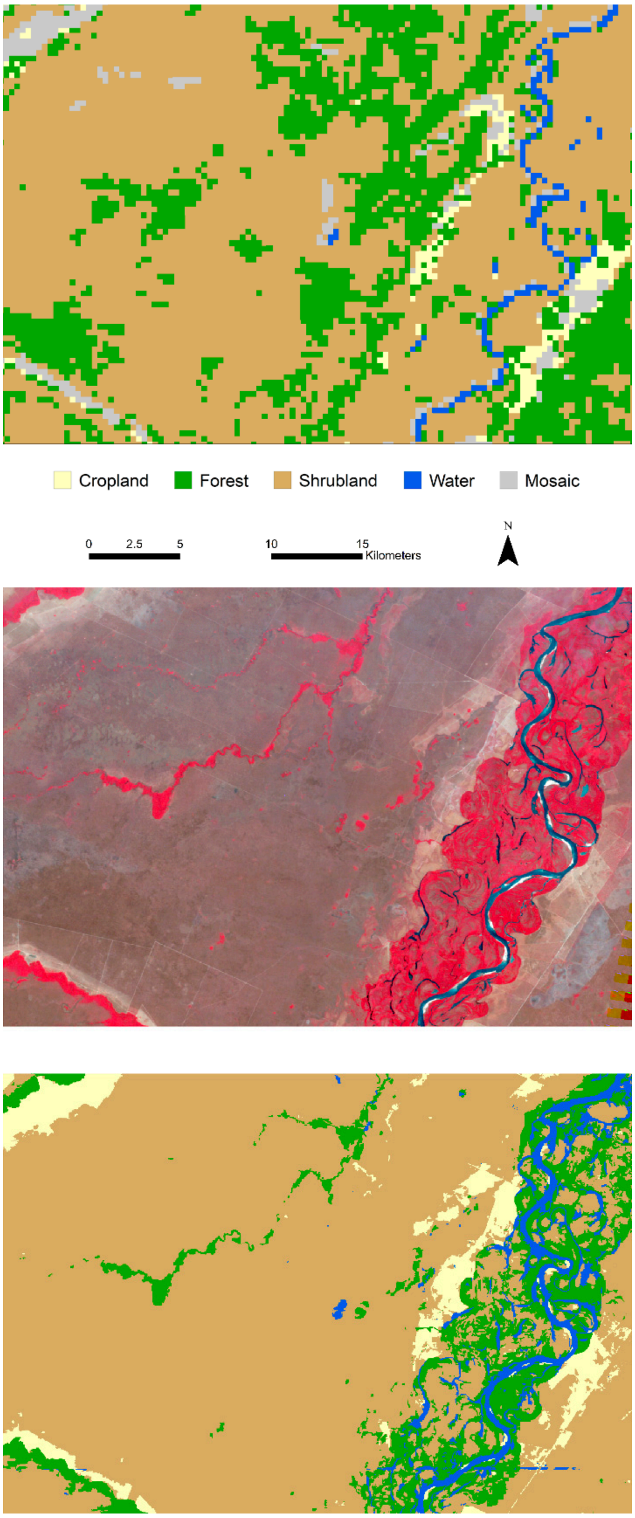

Figure 10. Closer view of Sector E5 on Figure 4, comparing GlobCover 2009 (**top**), Landsat 5 (**middle**) and BULC-U 2009 (**bottom**). The Landsat image is from 12 September 2010.

4. Discussion

The BULC-U 2009 classification represents a successful fusion of the high-quality labeling of the GlobCover project with the finer-resolution spatial information available from Landsat-class imagery. In this aspect, the BULC-U algorithm is reminiscent of the well-known pan-sharpening process, but for sharpening classifications rather than raw imagery. The specific effect of BULC-U is to tap scene-wide pixel-label information that is encoded in the relatively coarse GlobCover 2009 information and fuse it to higher-resolution spatial information taken from Landsat imagery. In this study, the spatial structure was interpreted using multiple Landsat color bands; although we have not attempted it here, it is conceivable that an even finer-scale product could be attempted by fusing GlobCover imagery with pan-sharpened Landsat or Sentinel-2 data.

4.1. Accuracy Improvements from BULC-U

The accuracy of the final BULC-U land cover product is considerably higher when compared to that of the original GlobCover 2009 classification from which it was built (Table 2). The improvement in accuracy appears to be due to two factors: First, the BULC-U algorithm was able to effectively 'repair' many inaccurate GlobCover 300-m scale pixel classification labels. In ingesting information from an Event, BULC-U treats the pixels of a given unsupervised cluster as likely being from a single LULC class. Over the course of ingesting the Events, this allowed pixels with incorrect labels in GlobCover to be gradually labeled like other pixels that shared their spectral characteristics. BULC-U also had a similar effect for areas labeled as Mosaic in GlobCover and marked as NoData by us when preparing the BULC-U run. These areas were gradually labeled like other pixels that shared their spectral characteristics at the finer 30-m scale. Second, the improved resolution of the Events used in this demonstration of BULC-U also played a role in the increased accuracy, by allowing finer-scale delineation of land cover within pixels whose LULC was heterogeneous at the 300-m scale. This was particularly relevant for 300-m pixels labeled by GlobCover as "Cropland" that contained, say, 80% Cropland and 20% Forest.

The specific ways that BULC-U improved accuracy are illustrated by a closer view of the study area in the GlobCover and BULC-U classifications, in sectors B5, B2, and E5 (Figures 8–10). Sector B5, which GlobCover had classified as predominantly Forest (with some Shrubland), BULC-U classified as predominantly Shrubland (Figure 8). BULC-U correctly identified most of Sector B2 as Cropland (Figure 9), including a substantial area that had been misclassified Shrubland or Forest in GlobCover. BULC-U also labeled much of the central part of B2 as more highly fragmented forest, and properly classified the GlobCover's Mosaic classes. GlobCover 2009 classified most of E5 as Forest, while BULC-U identified it as being predominantly Shrubland (Figure 10).

4.2. Fusing Information from Different Sensors and Projects

The BULC-U algorithm allows users to create and update land cover classifications using the same legend as a previously created classification, but with higher resolution and, at least in the case illustrated here, considerably improved accuracy. Using BULC-U it should be possible to refine the GlobCover classification elsewhere or to downscale other high-quality coarse classifications. Once a classification is refined to a sharper resolution it should be possible, as in Cardille & Fortin (2016), to roll the classification forward in time to show updated land cover at finer resolution in areas that are changing—or backward to show LULC history in earlier periods. Although we have used segmented ISODATA-classified Landsat data here to drive BULC-U, the algorithm can be driven with classifications created by any viable method. As a result, other sensors (e.g., Sentinel-2) could also be included alongside Landsat to refine and update a BULC-U classification.

4.3. GlobCover 2009 as a High-Quality Data Source

The comparison between GlobCover 2009 and BULC-U 2009 should not be misconstrued as criticism of any aspect of the GlobCover approach or result. In fact, the refinement described here would not have been possible without the GlobCover 2009 serving as a base. The global classification GlobCover 2009 is a source of high-quality global LULC data that, although imperfect at a fine scale, provided a statistical and spatial framework that could be refined by BULC-U to create an even higher-quality classification of the study area. GlobCover may well be the best product available for some locations, but even if its resolution is coarse for a given application, it can still be useful. Here, it is valuable in two roles: First, as the reference classification against which to compare unsupervised classifications; and second, as the *a priori* estimate of LULC for the study area, before the incorporation of Landsat-based Events. As seen in this study, although GlobCover 2009 was not correct on a pixel-by-pixel basis, and was substantially incorrect in its assessment of LULC proportions, it was sufficiently correct to be used as a reference to create probabilities of each class for BULC-U.

4.4. Number of Unsupervised Classes for BULC-U

The number of classes in the unsupervised Event classifications must be identified by the user of BULC-U and adapted to the distinct spectral classes in the satellite image and the number of classes being tracked. In this study, choosing the number of classes to create the Events in BULC-U was done using trial and error. During the stage of determining how many classes to use for Events, we asked whether: (a) for each of the unsupervised classes, each segment of a given class appeared to be the same LULC class in the Landsat image; and (b) the number of unsupervised classes was not excessively high to create instability in the transition matrices used by BULC. In our experiments, a too-large number of classes caused stray errors to appear unacceptably often in the output BULC-U classification, (e.g., stray clouds were displayed as Water). An Event classification with a too-small number of classes (e.g., 5 or fewer unsupervised classes) caused the resulting BULC-U classification to be less accurate, due to Event classes spanning multiple base classification classes—for example, containing both Forest and Shrubland. We advise that other users of BULC-U start with 20 unsupervised classes in a process of trial and error for creating Events.

4.5. Strengths of the BULC-U Method

The BULC-U methodology presents a considerable improvement to the overall BULC process, substantially reducing the time needed to produce an accurate time series. The original BULC algorithm required supervised classifications having the same legends for each Event, a process that demanded substantial amounts of human intervention, knowledge of the study area, and processing time. The adaptation of BULC to use unsupervised classifications allows the rapid creation of Events needed for BULC's Bayesian logic, by allowing the spectral characteristics of the imagery to directly drive the resulting time-series classification. The ease with which BULC-U generated a plausible classification can be a useful complement or starting point for more labor-intensive efforts like MapBiomas [41], which leverage a large amount of regional expert opinion and close observation to produce classifications with more detailed classes, though with substantially more effort.

One possible fruitful use of BULC-U is to update classifications to different time periods than that of the base image. Because most of a sufficiently large landscape does not change across the span of a few years or even decades, it should be possible to use the GlobCover 2009 classification to update classifications to years other than 2009. Because the vast majority of LULC pixels would not have changed their proper label in the intervening year, the same process described here could be able to be applied to earlier or later images. In the simplest case, there is nothing in this methodology that should inhibit the use of GlobCover 2009 to inform a BULC-U built using 2011 or 2012 Landsat imagery. Using this same logic, it is worth exploring BULC-U's potential to "leapfrog" to earlier dates of interest—2002 or 1986, for example. Although this is outside the scope of this manuscript, exploring the limits of that hypothesis will be the subject of future work.

5. Conclusions

Using unsupervised segmented Landsat classifications and the BULC-U algorithm, we were able to create a spatially refined map that was consistent with, but considerably improved from, the LULC labeling of the GlobCover 2009 classification. Although this technique has been shown here using Landsat 5 images and GlobCover 2009, the BULC-U algorithm is robust and general enough to use any classification legend and any satellite data. Future studies with BULC-U could include data from multiple sensors, as was done by Cardille & Fortin [34] and in review by Fortin et al. [42]. Additionally, this study used the unsupervised ISODATA classification algorithm to produce Events, and future work might compare and contrast the influence of other classification algorithms on the resulting BULC-U results.

A significant strength of the BULC-U process is that the resulting product is not entirely new, but is instead built on a foundation of an older expert-created classification. BULC-U uses data that may not have been readily available at the time of the original LULC classification to create a hybrid product with finer resolution and greater accuracy that is still compatible with the original classification. Those who have been using global classifications can continue to do so (with the same categories as before, if desired) with a finer-resolution data set that is highly consistent with the coarser source. It also opens the door to using accurate older, region-specific classifications to create new or extended time series.

As the era of open data continues, much more satellite data are available to researchers than even in the very recent past. At the same time, researchers now have decades of experience using existing classifications in a range of studies, including LULC change simulation models, carbon accounting analyses, and hydrologic studies. As more and more data emerges from archives for researchers, there will be a high priority on creating new data products that extend existing work but preserve data continuity. As a straightforward process that requires only a modest amount of expert remote sensing knowledge, BULC-U may be useful for a large set of applications.

Author Contributions: J.L. initiated this work as part of his MS thesis at McGill University, and did the initial development and coding of BULC-U. J.L. produced the first report of the method. M.T.C. and J.A.C. redeveloped the draft for publication with J.L., including figure/table design and execution. All three authors contributed to revisions.

Funding: This research was funded by a Google Earth Engine Research Award to develop BULC-U in Earth Engine.

Conflicts of Interest: The authors declare no conflicts of interest.

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