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Overcoming the Boundaries of History: Extracting Land Use and Land Cover Features from Archival Maps of Northern Burkina Faso Using GIS Software

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Archival maps provide a valuable way to explore historical environmental data collected before the use of satellite imagery. Archival maps in their physical form cannot readily be used, however, beyond what the original cartographer intended. In this project, we describe a manual method to bring scanned archival maps into digital form using common tools in a geographic information systems (GIS) software platform. We rely on the important context of West Africa where a generation of geographers as part of the *Terroir* school worked with local agrarian communities to understand land use and land cover (LULC) dynamics. Specifically, we analyze archival maps of the Yatenga Province in Burkina Faso originally created by Jean-Yves Marchal, who used aerial photography from 1952 and 1973. This article describes the image processing steps to extract LULC data from scanned archival images using the graphical user interface of popular GIS tools. We compare our results to Marchal's original maps and provide an alternative analysis of LULC change in the region using the newly extracted LULC data. **Key Words: archival maps, Burkina Faso, image processing, LULC, *Terroir* school.**

Historical maps can show patterns of environmental change over time. As visual tools, hard-copy maps can quickly and efficiently convey spatial information about agricultural expansion, forest conversion, or other types of land use and land cover (LULC) transitions. Analysis of hard-copy maps is difficult, however, because users are limited by the fixed nature of physical sheets of paper, and it is challenging to do much more than the original cartographer intended. In the era of satellite imagery, it is possible to analyze LULC change using space-based imagery, which is widely available for most of the planet. Prior to the 1970s, though, hand-drawn maps were used to depict land cover, land use, and land change. The historical record of remotely sensed imagery is limited, irregular, and contingent on the interests of historical actors in specific places. Additionally, before the computational power to analyze such imagery existed, categorizing LULC features on an image was performed manually using aerial photography. Today, historians, archaeologists, and other humanistic researchers are increasingly interested in using geographic information systems (GIS) to analyze historical information combining social and demographic information with spatial data (Gregory and Healey 2007; Knowles 2008; Schuppert and Dix 2009). If we wish to analyze these deeper historical data, we need to bring them into digital form.

Digitally analyzing archival maps poses unique challenges depending on how the maps were originally created, and researchers have approached these challenges in various ways. Previous scholars have explored long-term LULC change by meticulously digitizing features on historical maps, thereby creating a new data set based on an archival reference (Petit and Lambin 2002). This approach is successful but can be time consuming depending on how many historical maps are of interest. Advances in computer vision and image segmentation methods have made automatically extracting features from historical maps possible (Leyk and Boesch 2010; Chiang, Leyk, and Knoblock 2013). For example, Maxwell et al. (2020) relied on deep learning semantic segmentation methods to extract mining disturbance patterns from historic topographic maps of Appalachia in the eastern United States. They train a deep learning algorithm to predict whether a pixel belongs to a mine disturbance class or not. This approach, however, requires knowledge of specialized computational techniques that could act as a barrier for non-GIS and non–remote sensing specialists.

We aim to provide a different approach using built-in tools commonly available in popular GIS software with a graphical user interface. In this project, we demonstrate a novel method to extract LULC from archival maps by removing lines, text, and other features not relevant to LULC analysis. We rely on manually created maps of LULC in Burkina Faso, West Africa. This article presents the steps used to convert digital archival maps into GIS layers that enable further spatial analyses, like the change of LULC over time, as well as certain challenges faced during the process. We aim to make this approach replicable for those coming from disciplines in the humanities or social sciences with interests in GIS.

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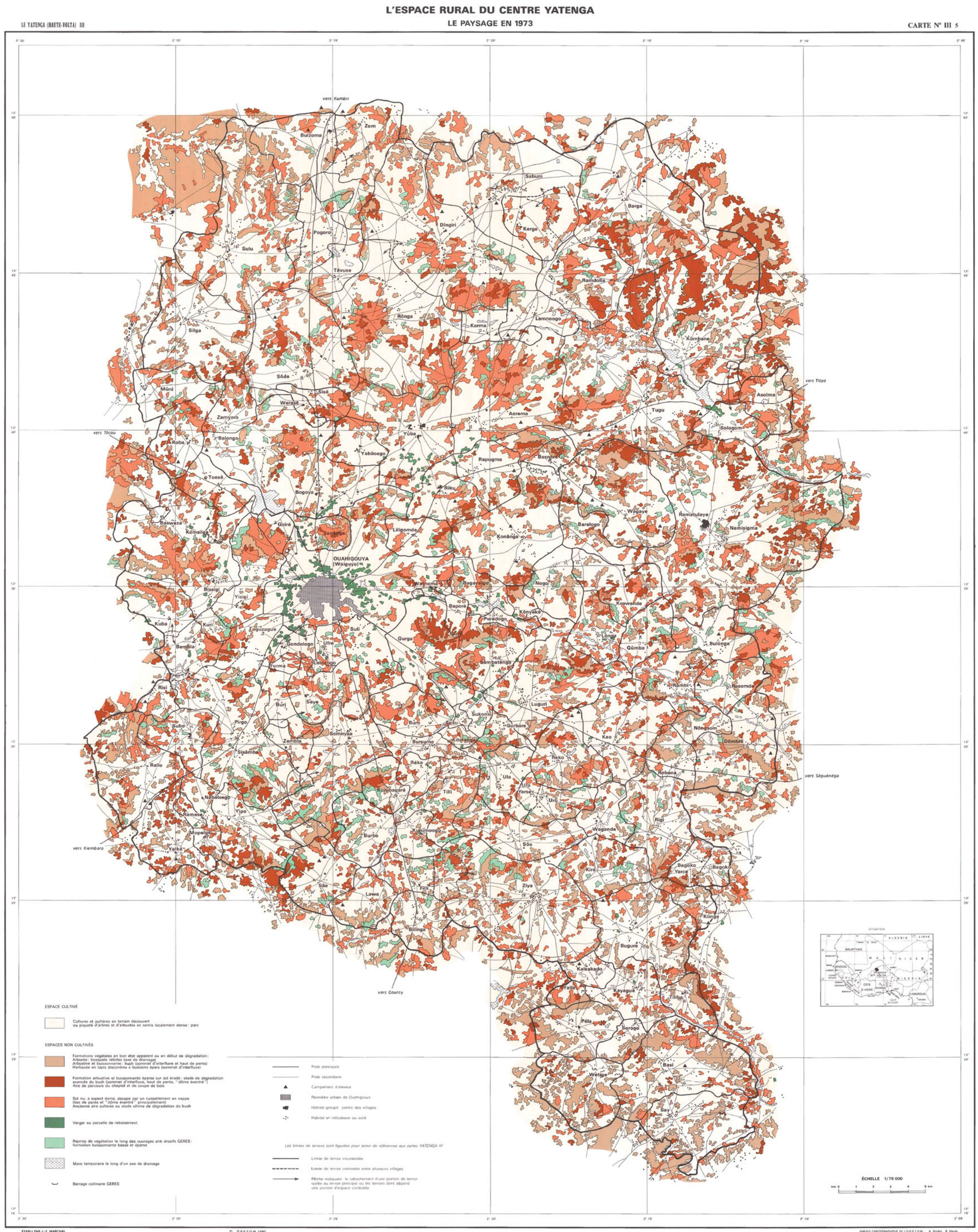

Figure 1 *Original 1973 Yatenga map by J. Y. Marchal (1983).*

This project uses Marchal's (1983) influential analysis of LULC change in the Yatenga Province of northern Burkina Faso (Figure 1) as a starting point. Marchal was a French geographer who studied the impacts local farming communities had on their environment. He tracked changes in land degradation, rehabilitation, and land use from 1952 to 1973. Marchal's work has been central to understanding historical dynamics of land use change in this region. The study presented here expands on his work using GIS software to perform spatial analyses that were not possible at the time he conducted his research.

We explain the conversion of two scanned archival maps into classified raster data. Next, we describe the degree of agreement of the resulting raster map to the original data. We end by reporting on changes in LULC for the region of Tugu in northern Burkina Faso.

Marchal and the *Terroir* School of French Geography

The *Terroir* school was initiated by geographers within the French Overseas Scientific and Technical Research Office (ORSTOM) in the 1960s and persisted into the mid-1980s. It represented a novel and innovative approach to applied research and development because its members established structured and systematic fieldwork methodologies that enabled controlled comparisons among different agrarian systems across West Africa and Madagascar (Bassett, Blanc-Pamard, and Boutrais 2007). Detailed maps were a critical component of these studies, and each research project was published as an atlas. Individual villages were often the focus and their *terroir* was constituted as the territorial limit of social and agricultural activities for members of these communities. The *Terroir* school was tremendously influential and informed development initiatives across West Africa. In particular, these works contributed to the *gestion de terroir villageois* (village territory management) approach whereby donors, governments, and nongovernmental organizations devolved decision making, design, and implementation to individual communities as part of a larger process of decentralization (Painter, Sumberg, and Price 1994). Overall, ORSTOM researchers produced twenty-six case studies consisting of both detailed descriptive text and cartographic figures (Bassett, Blanc-Pamard, and Boutrais 2007).

The published reports included dozens or even more than 100 maps as either in-text figures or folded plates in an annex. These thematic maps ranged in scale from 1:5,000 to 1:2,000,000 and visually displayed the distribution of population density, LULC, soil types, and numerous other agrarian characteristics. Some were produced as black-and-white images using different types of texture. Others were elaborate color plates. The reports themselves are available as .pdf files for download on the French Institute for Development Research (IRD) Horizon Web site (https://horizon.documentation.ird.fr/). Individual plates can also be searched and downloaded as .pdf files from the IRD SPHAERA cartographic database (http://sphaera.cartographie.ird.fr/). A simple search using the keyword *paysage* (or landscape) and *carte* (or map) returned more than 100 .pdf files available for download from SPHAERA. Of these, approximately thirty-five were maps of agrarian structures in Africa that dated from 1962 to 1995.

Marchal was a prominent geographer in the ORSTOM *Terroir* school. His 1983 *Yatenga Norde Haute Volta: La Dynamique d'Un Espace Rural Soudano-Sahelian* epitomizes their approach. The book features 842 pages of text, 106 tables, 47 black-and-white photographs, and approximately 145 maps. Some of the maps appear in the text and most are featured in the thirty-five plates. His work raised the alarm on desertification in the Yatenga region of northern Burkina Faso (then Upper Volta) and attracted development interventions to combat it (Reij, Tappan, and Belemvire 2005). Like other *terroir* school geographers, Marchal laboriously mapped LULC for Yatenga using matched aerial photographs from 1952 and 1973. This resulted in two detailed 1:75,000 landscape maps for central Yatenga showing the spatial distribution of LULC for the two time periods (CARTE No. III 4 and CARTE No. III 5). His innovative use of aerial photography was incorporated into the participatory methods implemented by development organizations to promote soil and water conservation projects throughout northern Burkina Faso in the 1980s through 2000s (Batterbury 1998). Our goal is to bring these archival maps back to life and present a methodology that could be used for other *terroir* and archival maps as well.

Methods

Our goal was to transform a .jpg file of the original scanned maps into data that could be analyzed using GIS software (Environmental Systems Research Institute [ESRI] 2019). This section describes the steps used to produce a newly classified image free of text, lines, and other data not needed for LULC analysis.

Obtaining Spatial Data from a .jpg File

First, high-quality .pdf files of the scanned maps (from 1952 and 1973) were obtained from the IRD SPHAERA Web site (IRD 1998, 2014; Zaiss 2014). We then converted these maps into .jpg files. Next, we used the Python computer vision library, OpenCV (Version 2.4.13.2; Bradski 2000), to reduce noise (i.e., reduce random variation in pixel values) in the image, relying on the non-local means denoising algorithm (see Appendix; Bradski 2000). This algorithm applies windows around pixels in the image, creating patches. For a specific pixel, it creates a window around the pixel in question, finds similar patches in other parts of the image, averages these patches' values, and replaces the pixel in question with the resulting average. This was necessary to make features on the image as distinct and spectrally uniform as possible. Then, we extracted the

Color	English Name	Description	French Name	Description
	Agriculture	Cultivated spaces, fallow, parkland	*Espace cultivé*	*Culture, jachères en terrain decouvert, parc*
	Eroded Soil	Bush showing advanced degradation, rangelands with wood-cutting	*Formation arbustive et buissonnante èparse sur sol érodé*	*Dégradation avancée du bush, aire de parcours du cheptel et de coupe de bois*
	Bare Soil	Previously cultivated area with compacted soil prone to sheet erosion	*Sol nu; ancienne aire cultivée; stade ultime de dégradation*	*À aspect damé, décapé par un ruissellement en nappe*
	Vegetation	Vegetated areas with scattered trees, bushes and grasses; exhibit incipient degradation	*Formation végétales en bon état apparent; en début de dégradation*	*Arborée, arbustive et buissonnante, herbacée en tapis discontinue à buissons épars*
	Orchard	Orchard or reforestation area	*Verger*	*Verger ou parcelle de reboisement*
	Re-vegetated	Low-lying sparsely wooded area	*Reprise de vegetation*	*Formation buissonnante basse et éparse*

Figure 2 *Classes for Marchal's 1973 map. Orchard and Re-vegetated were not featured in the 1952 map.*

red (R), green (G), and blue (B) channels of the file that, when combined, created the RGB color composite image. This resulting raster file became the base data set used as the primary input. A raster file is any data that is represented as a matrix (or grid) of pixels organized in rows and columns.

Next, the raster was georeferenced using ESRI's ArcGIS Desktop 10.7.1 software. Georeferencing refers to "the process by which a scanned [map] is processed into a digital raster map with geographic coordinates defined in a contemporary geographic reference system" (Affek 2013, 376). Georeferencing was completed by adding four evenly dispersed ground control points that match intersecting graticule lines on the original map with their known positions of latitude and longitude. The transformation specified was a first-order polynomial transformation. This step allowed us to give the raster a spatial reference (using the World Geodetic System 1984 spatial reference system and geodetic datum). The cell size of this resulting raster is 0.000059 degrees and, when projected to UTM Zone 30 N, 6.4 m. To test the accuracy of our georeferencing method, we calculated the root mean square error by matching graticules on the source map to four known and evenly dispersed longitude and latitude coordinates not included in the original georeferencing task. The 1952 and 1973 maps resulted in a total root mean square error of 0.000057 and 0.00019 decimal degrees, respectively. The georeferenced raster was then converted to a GeoTIFF file, which stores all coordinates so that the data could be imported into other GIS projects and applications.

Because the original map included features such as the legend and white background, we needed to exclusively extract the map to the extent of the region's boundary. Before extraction, we digitized the entire boundary line of Yatenga Province to create a new polygon. This polygon feature was used to clip (using the Extract by Mask tool) a new raster layer containing only pixels contained within the Yatenga boundary.

Unsupervised Classification and Reclassifying

To convert the raster data to distinct classes, such as agriculture and degraded soil, we used an unsupervised classification method. Unsupervised classification ("Iso-Cluster Unsupervised Classification" in ArcMap 10.7.1) assigns a user-defined number of classes to the data based on the clustering of the scanned values of the image. This method results in a new image with newly classified data. It converts the georeferenced raster to a classified raster where each pixel features a single value, which corresponds to its class.

For example, Marchal defined seven separate classes in the original 1973 map (Figure 2). Because random variation in pixel brightness values exists all throughout the image, even after noise reduction, the unsupervised classification technique will inevitably misclassify certain pixels (Figure 3). To account for these classification errors, we selected a larger number of clusters, specifically twenty clusters, than the number of classes desired. This approach gives the user more flexibility to merge misclassified pixels if they belong to the same

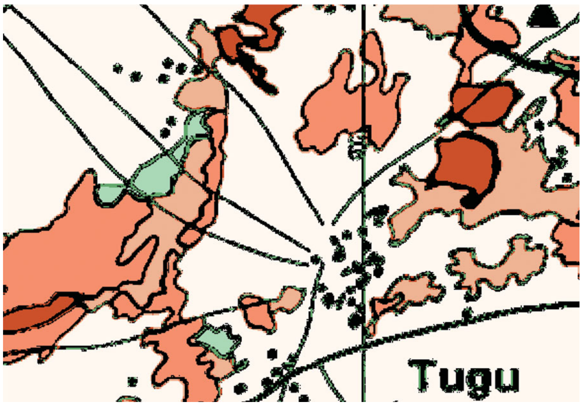

Figure 3 *Impacts of "noise" in the data after performing a classification method. Note the mixing of black and green pixels in labels and lines.*

predefined class as from the original map. Otherwise, an unsupervised classification using only seven classes might create more incorrectly labeled classes in incommensurable categories than the use of twenty classes. To merge classes, we visually compared the newly created image of twenty classes to the original map, merging classes (using the "Reclassify" tool) that belong to the same LULC category, such as agriculture or bare soil. We merged these classes to obtain the seven classes in Marchal's original map. We then repeated the same process on the 1952 image.

Remove Text and Boundary Data

Because this study focuses on agricultural land use, degradation, and rehabilitation, one challenge entailed removing features not relevant for the LULC analysis. Features on the map considered unimportant for this study included village *terroir* boundaries, annotation (i.e., text such as the names of localities), roads, and trails. Marchal represented these features in black on the original map. After reclassifying the map, some of the black boundary lines and text were still incorrectly labeled, causing a mixing of black with other pixels (Figure 3). Thus, the next step was to remove as much of the black boundary lines and misclassified categories as possible.

To remove the unneeded data, we used ArcGIS's Nibble tool to assign text and boundary lines the values of its nearest neighbor. This method requires that we create a new layer and assign "No Data" to the classes represented by the color black. We then use this new layer and the previous raster as inputs for the Nibble tool. For example, if a cell is "No Data," then Nibble will select the closest surrounding cells and change the "No Data" cell to the surrounding cells' value. There were still some pixels throughout the image that were artifacts of lines and text (see panel 3 in Figure 4). To remove these remaining artifacts, we used the Focal Statistics tool, which applies a filter across an image to smooth the results, converting pixels within a filter to the class by which they are surrounded based on certain criteria (see Figure 4). The Focal Statistics tool relies on a moving window with a specific shape to determine the value of pixels in the image. The choice of shape plays a role in how pixels are classified. We ran the Focal Statistics tool three times with a majority filter, first with an annulus (inner radius = 1, outer radius = 15) as the shape of choice and then with annulus (inner radius = 1, outer radius = 5) again to remove remaining line artifacts and with wedge (radius = 3, starting angle = 0, ending angle = 45) to help fill in "No Data" pixels resulting from the previous two passes.[1] See Figure 5 for all image processing steps using ArcMap 10.7.1.

These steps significantly reduced the artifacts of text and boundary data in the final classified raster. We performed this process for both maps. These filter operations created slight modifications throughout the image, leading to the next question: How accurate was this procedure? The following section describes our method to test for degree of agreement.

Methods for Measuring Agreement

A common practice to assess how well a classified map corresponds to the original data is to perform an analysis of agreement, which compares classified pixels to known points in the original reference data using an error matrix (Foody 2002). Scholars have addressed limitations of other approaches, often called "accuracy assessment" in remote sensing studies, that use a Kappa index (Foody 2002, 2008, 2020; Pontius and Millones 2011; Comber et al. 2012). Kappa is an index of agreement between two maps that has been used to quantify the degree to which the agreement is greater than what could be achieved by random chance. Scholars, however, have criticized the formula for calculating kappa as an

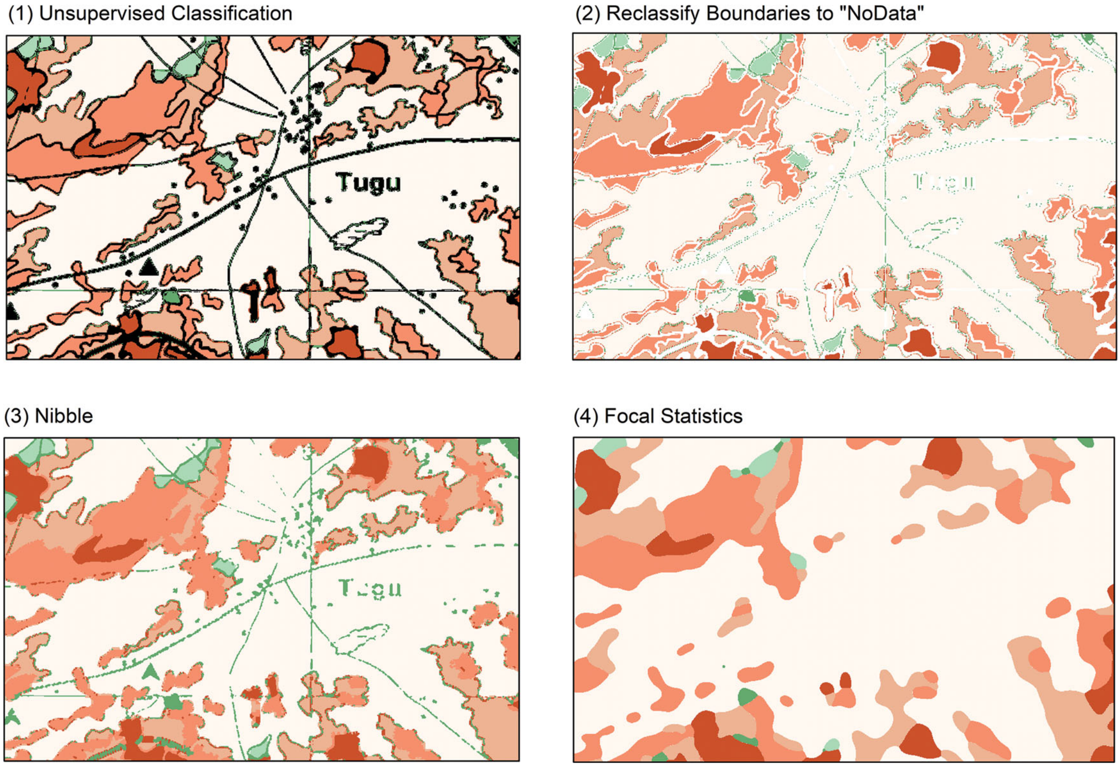

Figure 4 *A breakdown of the different image processing steps.*

incorrect formulation of chance correction, and thus the results are potentially misleading (Foody 2020). Instead, simpler measures of agreement have been put forward. In this project, we rely on two simpler metrics: quantity disagreement and allocation disagreement (Pontius and Millones 2011). Quantity disagreement is the amount of difference between a reference map and a classified map due to mismatches between the categories. In other words, this quantifies how many pixels were mislabeled in the classified map compared to the reference map. Allocation disagreement is the difference between a reference map and a classified map due to mismatches between the spatial allocation of certain categories. In other words, this quantifies the disagreement in the spatial distribution of mislabeled pixels between the reference and classified maps.

We rely on an error matrix to report the total number of points classified correctly and incorrectly. We chose the *terroir* of Tugu because the community figured prominently in Marchal's (1983) study. His book included large-scale printed maps and tables of LULC change for Tugu. We detail this method for the *terroir* of Tugu (Figure 6).

To obtain reference data, we digitized the *terroir* of Tugu on Marchal's 1973 map, producing a new polygon feature class and adding attributes for each feature within this layer. These attributes correspond to the original LULC classes in Figure 2.

The classified data were the output raster data from the image processing steps described in the previous section.

Analyzing agreement between two maps entails collecting reference points and comparing them to the classified data. We transformed the reference polygon data into raster format, with the same cell size as the original map, and created a point for every pixel. We clipped and aligned the classified data to the reference data using "Extract by Mask." Reference points were compared against the classified data to produce a cross-tabulation or an error matrix (see Table 1).

Finally, we used equations detailed in Pontius and Millones (2011) to compute quantity disagreement and allocation disagreement for each category. Because these equations report counts of points, it can be difficult to compare across categories if one of the categories is extremely large, as was the case for agriculture. We then computed relative disagreement metrics for each category using methods described in Warrens (2015). This final step allows the reader to easily compare across categories.

Methods for Change Detection

Marchal's two maps from 1952 and 1973 enable the detection of LULC change between the two time periods. Detecting LULC change is defined as observing differences in features at different time

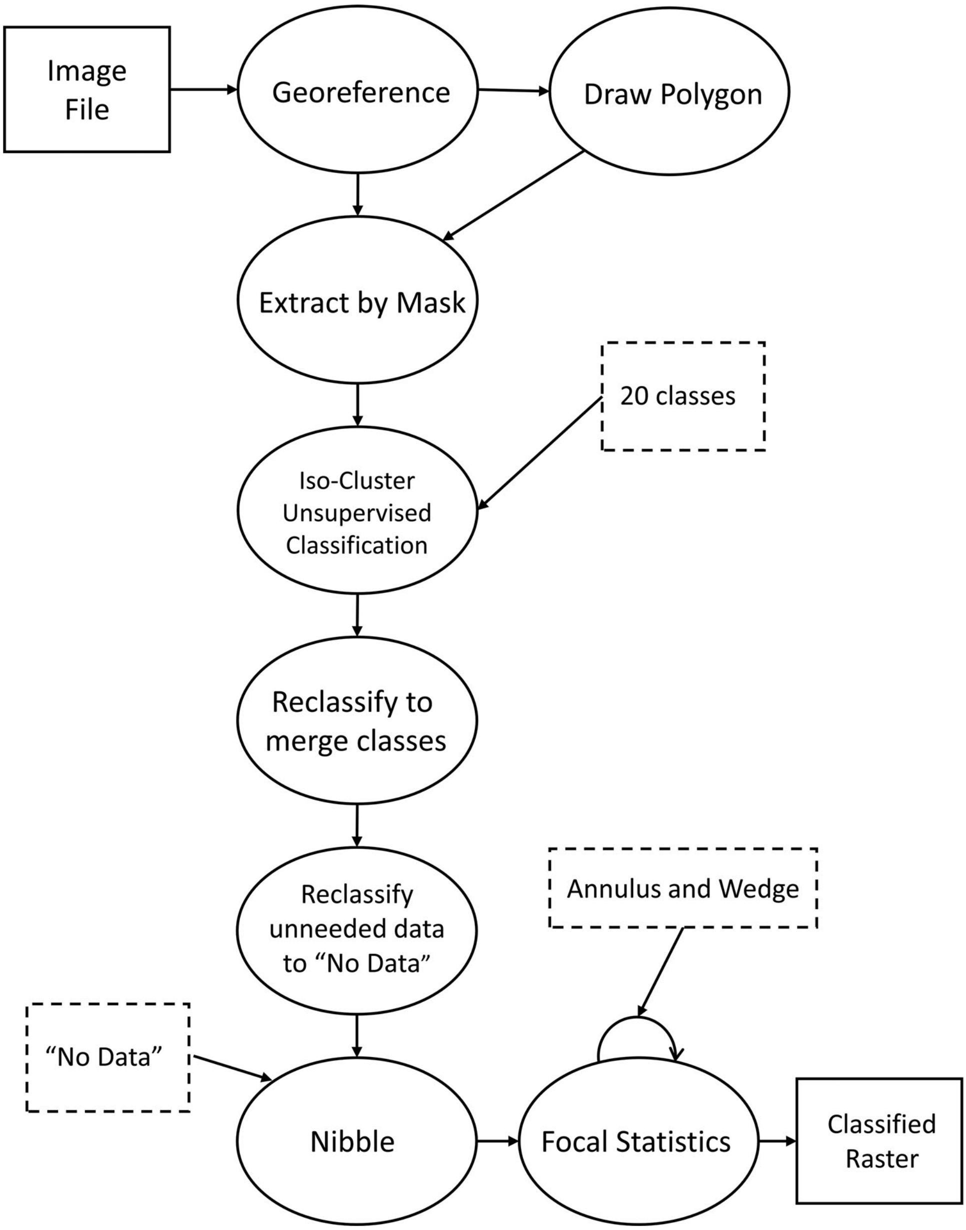

Figure 5 *Image processing techniques used to convert .jpg file to georeferenced raster image and to remove boundary, text, and locality data not necessary for land use, land cover analysis.*

periods (Singh 1989). This study relies on a pixel-based change detection method by comparing changes in individual pixel values (cf. Tewkesbury et al. 2015). For instance, we can discern which pixels changed from agriculture to bare soil and quantify the number of pixels that did so. Moreover, we can also identify spatial clusters in the data and visualize them. This is important because, at the time, Marchal (1983) only reported the percentage of increases of certain classes (Table 2) but not the trajectory of class change; that is, answering the question, "What changed to what?"

To perform this pixel trajectory method (Wang et al. 2012), we reclassified the 1952 raster by assigning single-digit numbers (1–6) corresponding to the individual LULC classes and multiplying by ten (creating 10, 20, … , 60). Then, we classified the subsequent 1973 image using the leading values of the 1952 image (1, 2, … , 6). Next, we used a raster calculator to add both layers in ArcMap, creating a new raster image of added values (e.g., 11, 23, 14).

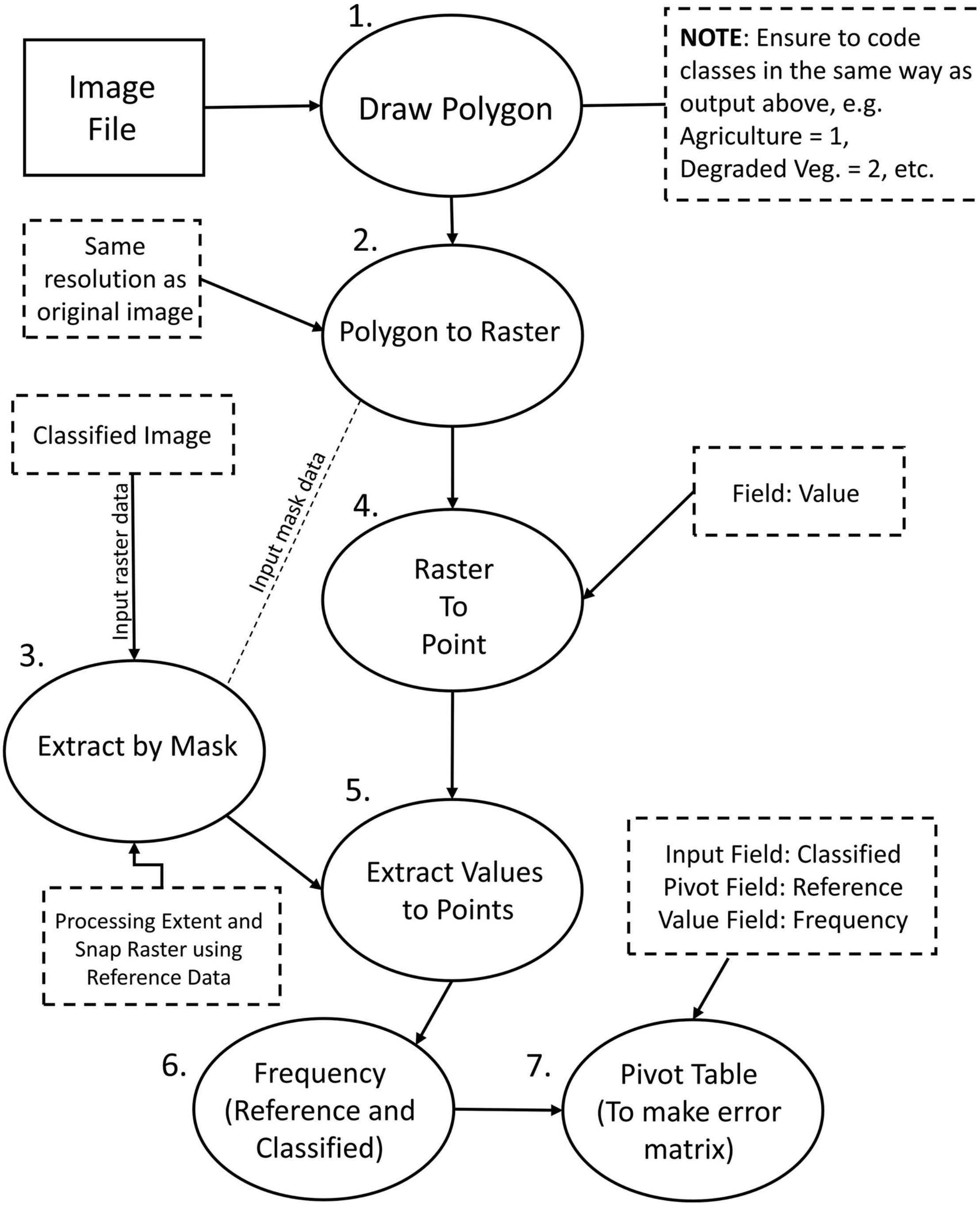

Figure 6 *Analysis of agreement steps.*

This newly created raster image tracks change over time by specifying the first class in the tens digit and the second class in the ones digit; for example, a change from Class 1 to Class 3 is represented by 13, but an 11 means the class stayed the same (see Figure 7). Results from this process were used to visualize areas converted from agriculture to bare soil.

Results

Image Processing Results

Visually speaking, we successfully removed the text, labels, and boundary lines (Figure 8). If these had not been removed, there would have been interferences with the text, label, and line class represented

Table 1 *Error matrix with absolute count and proportion (in parentheses) of reference points for Tugu, 1973*

	Reference							
Classified	**Agriculture**	**Deg. Veg.**	**Bare Soil**	**Veg Non-Deg.**	**Orchard**	**Re-veg**	**Other**	**Total**
Agriculture	668,283 (51.8%)	4,394 (0.34%)	15,725 (1.22%)	22,179 (1.72%)	3,168 (0.25%)	2,808 (0.22%)	7,997 (0.62%)	724,554 (56.1%)
Deg. Veg.	2,837 (0.22%)	126,410 (9.79%)	5,258 (0.41%)	9,613 (0.74%)	0 (0.00%)	194 (0.02%)	0 (0.00%)	144,312 (11.2%)
Bare Soil	13,580 (1.05%)	6,054 (0.47%)	131,872 (10.2%)	15,647 (1.21%)	83 (0.01%)	1,118 (0.09%)	152 (0.01%)	168,506 (13.1%)
Veg Non-Deg.	10,898 (0.84%)	6,171 (0.48%)	1,988 (0.15%)	204,697 (15.9%)	0 (0.00%)	870 (0.07%)	0 (0.00%)	224,624 (17.4%)
Orchard	4,636 (0.36%)	1,119 (0.09%)	614 (0.05%)	4,417 (0.34%)	1,635 (0.13%)	3,745 (0.29%)	103 (0.01%)	16,269 (1.26%)
Re-veg	568 (0.04%)	223 (0.02%)	141 (0.01%)	552 (0.04%)	0 (0.00%)	11,336 (0.88%)	0 (0.00%)	12,820 (0.99%)
Other	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)	0 (0.00%)
Total	700,802 (54.3%)	144,371 (11.2%)	155,598 (12.1%)	257,105 (19.9%)	4,886 (0.38%)	20,071 (1.55%)	8,252 (0.64%)	1,291,085 (100%)

Table 2 *Quantity disagreement and allocation disagreement expressed in absolute and relative terms for analysis of agreement*

	Quantity Disagreement		Allocation Disagreement		
Class	**Absolute**	**Relative (%)**	**Absolute**	**Relative (%)**	**Overall Disagreement (%)**
Agriculture	23,752	1.67	65,038	4.56	—
Deg. Veg.	59	0.02	35,804	12.40	—
Bare Soil	12,908	3.98	47,452	14.64	—
Veg Non-Deg	32,481	6.74	39,854	8.27	—
Orchard	11,383	53.81	6,502	30.74	—
Re-veg	7,251	22.05	2,968	9.02	—
Other	8,252	100.00	0	0.00	—
Overall	48,043	3.72	98,809	7.65	11.37

Note: Absolute values represent number of pixels. Overall disagreement in the entire map is equal to overall quantity disagreement plus overall allocation disagreement.

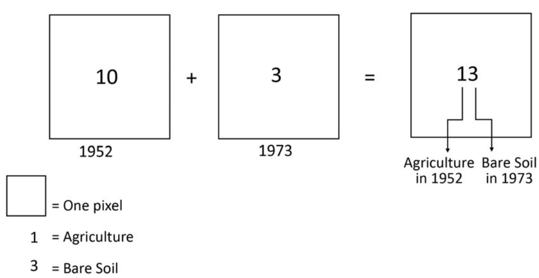

Figure 7 *Pixel trajectory diagram.*

by the color black. The agreement can be assessed for each category using the total number of classes (and proportions in parentheses) in the error matrix in Table 1 as well as the relative disagreement metrics in Table 2. The four most commonly occurring classes had relatively good accuracies during classification. The relative measure for quantity and allocation disagreement will be closer to 100 percent if there was complete disagreement between the reference and classified maps. Thus, a lower percentage means a higher degree of agreement. Agriculture, degraded vegetation, bare soil, and vegetation had low values of 1.67, 0.02, 3.98, and 6.74 percent, respectively, for quantity disagreement. This means that for each of these four categories, the number of pixels classified as each class is close to the number of that class in the reference map. In terms of allocation disagreement, agriculture and vegetation had low values of 4.56 percent and 8.27 percent, respectively. This indicates that other classes did not get mislabeled as agriculture or vegetation very often, and the classified image reported these classes with high spatial agreement with the reference data. Bare soil had a slightly elevated allocation disagreement of 14.6 percent. This is likely due to either the mislabeling of classes after the unsupervised classification or small errors in class labeling during each pass of Focal Statistics that modified the edges of various classes. The overall disagreement of the classified map to the reference map was 11.37 percent, which is the sum of the overall quantity disagreement (3.72 percent) and the overall allocation disagreement (7.65 percent).

On the other hand, some classes did not perform well due to either errors in class labeling during image processing, their relatively small area, or the class not being distinct enough to be identified by

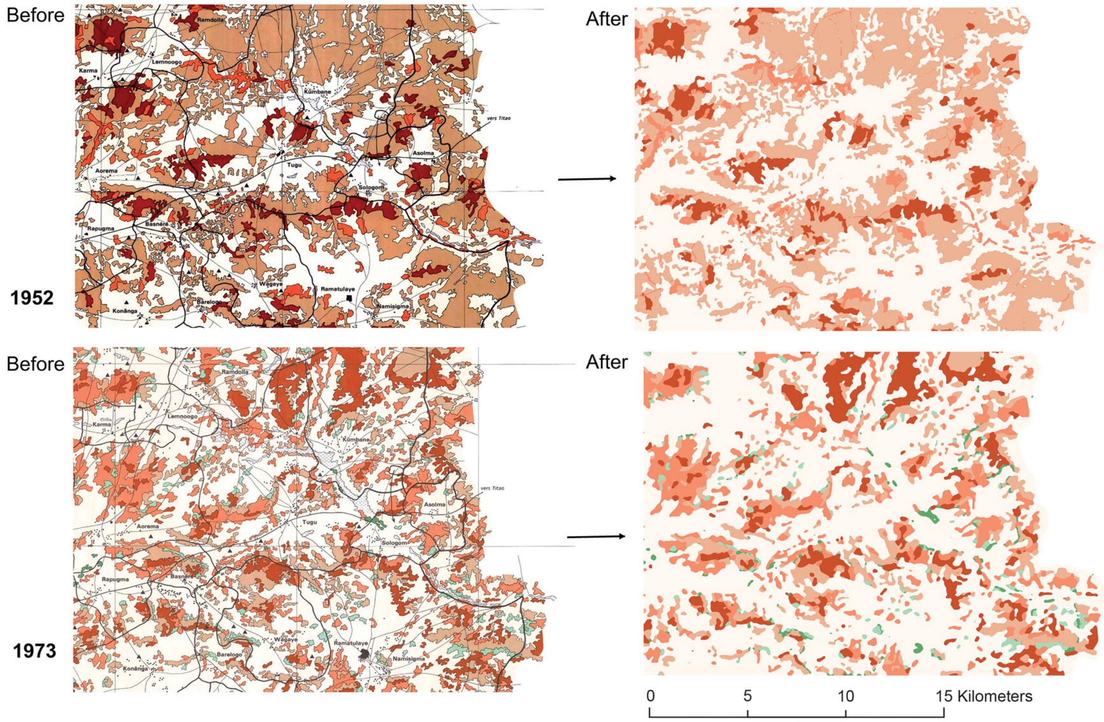

Figure 8 *Image processing, before (left) and after (right), of an area of Tugu, Yatenga.*

the classification algorithm. The classes with the highest levels of quantity disagreement were orchard and other with values of 53.8 and 100 percent, respectively. This happened for two separate reasons. For the orchard class, the likely reason is that its area was small from the start and the image processing steps diminished some area around its edges. Orchard's allocation disagreement, moreover, was 30.7 percent, due to artifacts of boundary lines that were incorrectly classified during the classification algorithm step (see Figure 9). The reason the category of other has such a high quantity disagreement value, despite its very small area, is because it was all converted to agriculture. This happened because the original category was demarcated by black lines that were removed with the text, label, and line class. Its allocation disagreement is 0 percent, which is erroneous because there were zero pixels of this category in the classified image. The conclusion here is that classes with very small areas might perform less than optimally during image processing but more abundant areas were faithfully preserved. In the context of Yatenga, we are interested in measuring agricultural change to bare soil, which is now possible given the relatively accurate results for these specific categories.

Change Detection Results

Marchal originally reported increases and decreases in LULC area for the Tugu region (Table 3). We extend his original analysis to determine the trajectory of LULC change; that is, what changed to what? Marchal calculated an increase in bare soil from 2.2 to 10.4 percent of the regional area (a 470 percent increase in bare soil). In comparison, our analysis shows an increase from 9.23 to 13.10 percent of the regional area (a 141 percent increase in bare soil). Although our results differ from Marchal's, they follow the same directions and are on the same order of magnitude. For example, in both our and Marchal's analyses, the vegetation class decreases, whereas all other classes increase. Differences between our analysis and Marchal's are due to incorrectly labeled classes during image processing and the way our boundary for Tugu was manually drawn versus that of Marchal. For example, portions of the line class for the 1952 data were incorrectly classified as bare soil, which changes the percentage of total bare soil area for that year. Additionally, slight differences in the way the border for Tugu was drawn result in different areas of LULC classes within the boundary. Barring these differences, we can have a more detailed understanding of LULC change over time by using pixel-based change detection.

Not only could we determine what changed but we also can visualize where these changes occurred. A pixel-based change detection analysis showed increases and decreases throughout the region of Tugu, especially increases in agriculture. Additionally, we can determine clusters of change

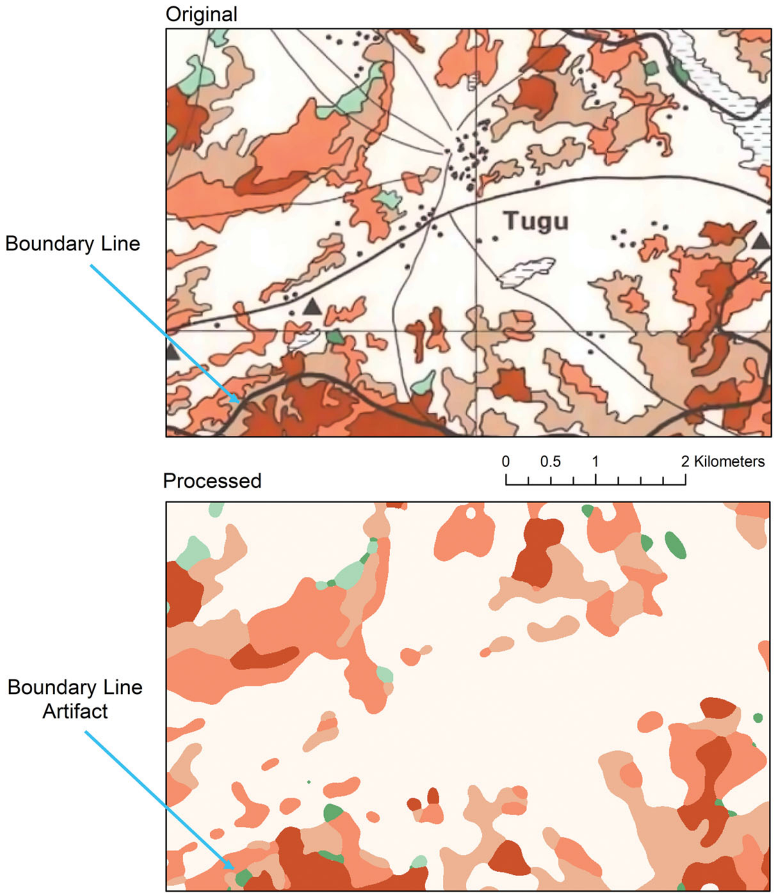

Figure 9 *Comparison of original map and processed map. Notice the line artifacts indicated by arrows.*

Table 3 *Marchal's (1983, 223) original analysis of LULC percentage area increases, 1952–1973, compared to the present analysis*

	Marchal (1983, 223)				Present analysis			
			Change (1952–1973)				Change (1952–1973)	
LULC	**1952 % Area**	**1973 % Area**	**% Area**	**Factor**	**1952 % Area**	**1973 % Area**	**% Area**	**Factor**
Vegetation	35.30	13.60	–21.70	×0.38	33.28	17.39	–15.89	×0.53
Degraded bush	3.90	7.00	+3.10	×1.80	5.03	11.17	+6.14	×2.22
Agriculture	58.25	65.25	+7.00	×1.11	52.46	56.13	+3.67	×1.07
Bare soil	2.20	10.40	+8.20	×4.70	9.23	13.05	+3.82	×1.41
Water bodies	0.35	0.75	+0.40	×2.00	NA	NA	NA	NA
Orchard	—	0.75	+0.75	—	—	1.26	+1.26	—
Re-vegetation	—	2.75	+2.25	—	—	0.99	+0.99	—
Urban	—	—	—	—	—	—	—	—
Total	100	100	±21.70		100	100	±14.74	

Note: Title of Marchal's original table: Comparaisons entre l'évolution des faciès à Tugu et au Centre-Yatênga. LULC = land use, land cover.

from one class to another by visually inspecting these patterns and quantifying them. In 1952, 52.50 percent of total area was agriculture and 5.35 percent of that total area became bare soil in 1973 (from agriculture in 1952), the biggest type of change for the agriculture class (Table 4). This apparent land degradation appears to have occurred in scattered areas (Figure 10). Although not explicitly visualized in the maps that follow, one other noteworthy type of change was from vegetation to agriculture, indicating that communities were converting much of the area to agriculture after 1952. This suggests that residents of Tugu were expanding agriculture by clearing preexisting vegetated areas. Agriculture also changed to orchards and revegetated areas, suggesting that

Table 4 *Change matrix for Tugu, 1952–1973*

	Class	1973 Agriculture (%)	Eroded soil (%)	Bare soil (%)	Vegetation (%)	Orchard (%)	Re-vegetated (%)	Total (%)
1952	Agriculture	38.70	2.81	5.35	4.79	0.60	0.26	52.50
	Eroded soil	2.03	0.59	1.48	0.74	0.17	0.02	5.03
	Bare soil	1.49	2.94	1.81	2.77	0.13	0.09	9.23
	Vegetation	14.00	4.83	4.40	9.09	0.36	0.63	33.30
	Total	56.10	11.20	13.10	17.40	1.26	0.99	100.00

Note: Percentages represent percentage of area for all Tugu. The table can be read from left to right. For example, looking at the 1952 rows and going from agriculture to bare soil means 5.35 percent of total area changed from agriculture in 1952 to bare soil in 1973. For agriculture, 38.7 percent of the total area remained the same. Due to the problem with artifacts from boundary lines and text, changes to orchard (1.26 percent of total area in 1973) are affected by these errors.

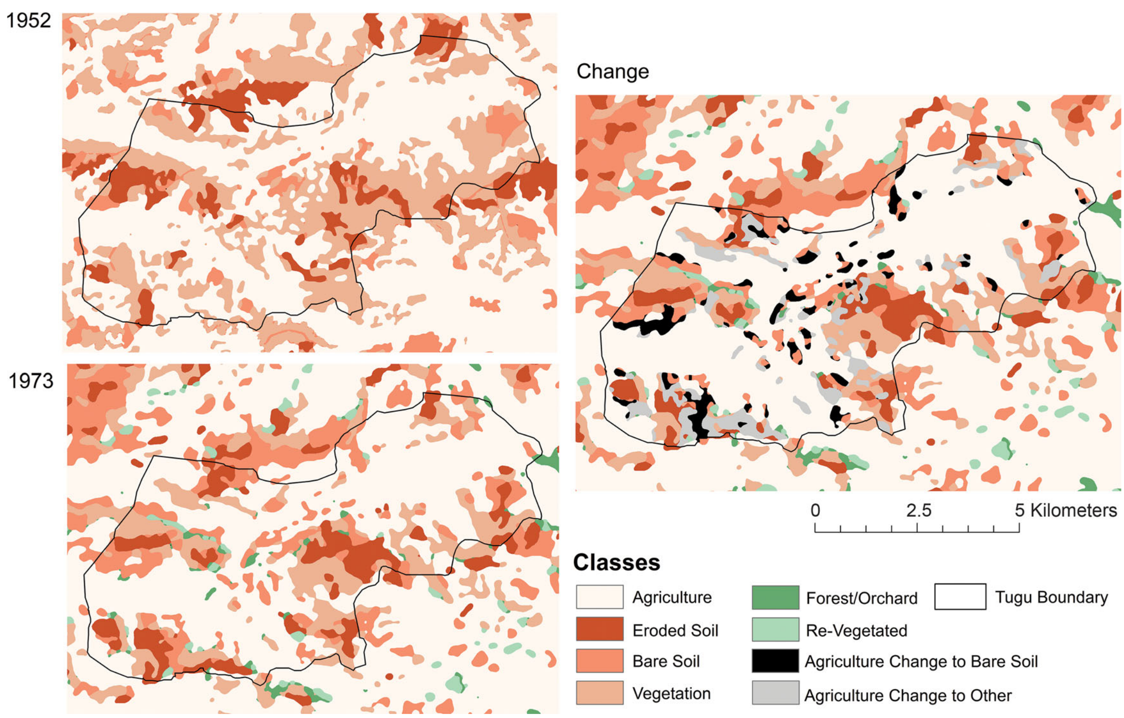

Figure 10 *Change detection analysis revealing changes to bare soil from 1952 to 1973.*

change was not only going in one direction toward degradation but toward rehabilitation as well (Table 4).

Limitations and Lessons Learned

Transforming an archival map using image filtering techniques can incorporate classification errors. For example, the image processing steps smoothed over and generalized original boundaries, leaving behind artifacts from labels or lines. Additionally, manually georeferencing one map to the other proved challenging as they did not align exactly. We performed several methods, like matching graticules to graticules on both maps, as well as roads to roads, but there were still minor differences throughout the image. Misalignment problems can have consequences for pixel-based change detection since the maps are compared pixel by pixel. To speculate why misalignment occurred, errors could be due to the way the original maps were printed. Given that our results were similar to Marchal's in magnitude and direction, we conclude that errors resulting from spatial misalignment are small. This is a judgment call, however, and a more accurate georeferencing technique might yield more accurate statistics. Spatial distortion can also be quantified by calculating the RMSE as discussed in the Methods section.

The use of a .jpg image created further complications. Because .jpg files are stored in a lossy format (i.e., information is permanently lost to compress the file), this can introduce artifacts (or distortions) in the file that might influence image processing. We encourage readers wishing to replicate this process to not use the .jpg format and to store the data in .tiff format instead, because the latter is usually lossless.

Each iteration of the Focal Statistics filter slightly modifies the image. We realized that “No Data” pixels resulted from the first and second pass of Focal Statistics due to there being more than one majority class inside a filter. We corrected for this by using the wedge filter to help fill in “No Data” pixels. There were still around twenty “No Data” pixels scattered around class edges that we manually filled in as the nearest largest class. Because these remaining “No Data” pixels were so few compared to the total pixel count, we concluded that any influence on results was negligible. Fine tuning the parameters of this image filter in this analysis or, perhaps, using another filter tool altogether might be more efficient and yield better results.

Conclusion

This project explored ways to convert scanned archival maps into georeferenced spatial data relying on the graphical user interface of common GIS software. Researchers interested in applying this method to other data sets might encounter unique challenges given specific presentations of archival maps. For example, although this project benefited from the unique color combination of Marchal’s original classes, maps with less distinct color schemes might be less suitable for unsupervised classification algorithms. Newer software packages (e.g., ArcGIS Pro) might offer a solution given developments in object detection techniques using deep learning (ESRI 2020). Additionally, the map we relied on was digitally rendered and downloaded, and we therefore did not have to scan the map manually. Other maps might exist as physical copies that need to be scanned using special equipment. Finally, we relied on the ArcGIS environment, but not everyone might have a license to use proprietary software. Open-source tools such as QGIS can offer similar techniques, such as the use of nearest neighbor filters to fill in “No Data” pixels and to remove unwanted artifacts (QGIS.org 2021).

Using the ArcGIS environment in ArcMap v. 10.7.1, we successfully transformed a .jpg file of a digitally rendered map by Marchal (1983) into spatially referenced rasters. Using a suite of image processing techniques, we were able to remove labels, boundary lines, and other noise from the original map to extract the LULC data of interest. This method makes possible a deeper understanding of historical environmental change through quantifying LULC trajectories and identifying where change occurred. This is significant in the context of the study of African environmental change because it allows scholars the possibility to look at environmental dynamics further back in time than is possible with satellite data. Other scholars can follow the steps presented herein to convert maps available not only in the IRD SPHAERA database (IRD 2014), where there are twenty-eight maps available for download from Marchal’s work, but from other archival sources, as well. Northern Burkina Faso has experienced complex environmental changes due to climate patterns and human-led conservation practices. The methods presented here give scholars and GIS users a novel way to use archival maps to augment their historical and environmental research. ■

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Note

[1] If there was more than one majority result from the Focal Statistics operation, the resulting value was “No Data.” We found that using the wedge shape helped fill in these scattered “No Data” pixels.

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Literature Cited

Affek, A. 2013. Georeferencing of historical maps using GIS, as exemplified by the Austrian military surveys of Galicia. *Geographia Polonica* 86 (4):375–90. doi: 10.7163/GPol.2013.30.

Bassett, T. J., C. Blanc-Pamard, and J. Boutrais. 2007. Constructing locality: The terroir approach in West Africa. *Africa* 77 (1):104–29. doi: 10.3366/afr.2007.77.1.104.

Batterbury, S. 1998. Local environmental management, land degradation and the "gestion des terroirs" approach in West Africa: Policies and pitfalls. *Journal of International Development* 10 (7):871–98. doi: 10.1002/(SICI)1099-1328(1998110)10:7 < 871::AID-JID533 > 3.0.CO;2-U.

Bradski, G. 2000. The OpenCV library. *Dr. Dobb's Journal: Software Tools for the Professional Programmer* 25 (11): 120–23.

Chiang, Y.-Y., S. Leyk, and C. A. Knoblock. 2013. Efficient and robust graphics recognition from historical maps. In *Graphics recognition: New trends and challenges*, ed. Y.-B. Kwon and J.-M. Ogier, 25–35. Berlin: Springer.

Comber, A., P. Fisher, C. Brunsdon, and A. Khmag. 2012. Spatial analysis of remote sensing image classification accuracy. *Remote Sensing of Environment* 127 (December):237–46. doi: 10.1016/j.rse.2012.09.005.

Environmental Systems Research Institute. 2019. *ArcGIS desktop: Release 10.7.1*. Redlands, CA: ESRI.

Environmental Systems Research Institute. 2020. *ArcGIS pro: Release 2.7.0*. Redlands, CA: ESRI.

Foody, G. M. 2002. Status of land cover classification accuracy assessment. *Remote Sensing of Environment* 80 (1):185–201. doi: 10.1016/S0034-4257(01)00295-4.

Foody, G. M. 2008. Harshness in image classification accuracy assessment. *International Journal of Remote Sensing* 29 (11):3137–58. doi: 10.1080/01431160701442120.

Foody, G. M. 2020. Explaining the unsuitability of the kappa coefficient in the assessment and comparison of the accuracy of thematic maps obtained by image classification. *Remote Sensing of Environment* 239 (March): 111630. doi: 10.1016/j.rse.2019.111630.

Gregory, I. N., and R. G. Healey. 2007. Historical GIS: Structuring, mapping and analysing geographies of the past. *Progress in Human Geography* 31 (5):638–53. doi: 10.1177/0309132507081495.

Institut de recherche pour le développement (IRD). 1998. Last modified June 15, 2017. Accessed January 20, 2018. http://sphaera.cartographie.ird.fr/.

Institut de recherche pour le développement (IRD). 2014. Yatenga: Nord Haute-Volta: La dynamique d'un espace rural soudano-sahélien: A set of 19 map sheets, Scale of 1:5 000 000 to 1:15 000 (data set). Date of publication: 1980. Project NumeriSud SPHAERA-GEO, Bondy, France. http://sphaera.cartographie.ird.fr/serv_horizon.php?num=1222.

Knowles, A. K. 2008. *Placing history: How maps, spatial data, and GIS are changing historical scholarship*. Redlands, CA: ESRI Press.

Leyk, S., and R. Boesch. 2010. Colors of the past: Color image segmentation in historical topographic maps based on homogeneity. *GeoInformatica* 14 (1):1–21. doi: 10.1007/s10707-008-0074-z.

Marchal, J.-Y. 1983. *Yatenga: Nord Haute-Volta. La dynamique d'un espace rural soudano-sahélien*. Paris: ORSTOM, Centre IRD de Bondy. http://www.documentation.ird.fr/hor/fdi:16610.

Maxwell, A. E., M. S. Bester, L. A. Guillen, C. A. Ramezan, D. J. Carpinello, Y. Fan, F. M. Hartley, S. M. Maynard, and J. L. Pyron. 2020. Semantic segmentation deep learning for extracting surface mine extents from historic topographic maps. *Remote Sensing* 12 (24):4145. doi: 10.3390/rs12244145.

Painter, T., J. Sumberg, and T. Price. 1994. Your "terroir" and my "action space": Implications of differentiation, mobility and diversification for the "approche terroir" in Sahelian West Africa. *Africa* 64 (4):447–64. doi: 10.2307/1161368.

Petit, C. C., and E. F. Lambin. 2002. Impact of data integration technique on historical land-use/land-cover change: Comparing historical maps with remote sensing data in the Belgian Ardennes. *Landscape Ecology* 17 (2): 117–32. doi: 10.1023/A:1016599627798.

Pontius, R. G., and M. Millones. 2011. Death to kappa: Birth of quantity disagreement and allocation disagreement for accuracy assessment. *International Journal of Remote Sensing* 32 (15):4407–29. doi: 10.1080/01431161.2011.552923.

QGIS.org. 2021. QGIS 3.16. Geographic Information System user guide. https://docs.qgis.org/3.16/en/docs/user_manual/index.html.

Reij, C., G. Tappan, and A. Belemvire. 2005. Changing land management practices and vegetation on the Central Plateau of Burkina Faso (1968–2002). *Journal of Arid Environments* 63 (3):642–59. doi: 10.1016/j.jaridenv.2005.03.010.

Schuppert, C., and A. Dix. 2009. Reconstructing former features of the cultural landscape near early Celtic princely seats in southern Germany: A GIS-based application of large-scale historical maps and archival sources as a contribution to archaeological research. *Social Science Computer Review* 27 (3):420–36. doi: 10.1177/0894439308329766.

Singh, A. 1989. Review article: Digital change detection techniques using remotely-sensed data. *International Journal of Remote Sensing* 10 (6):989–1003. doi: 10.1080/01431168908903939.

Tewkesbury, A. P., A. J. Comber, N. J. Tate, A. Lamb, and P. F. Fisher. 2015. A critical synthesis of remotely sensed optical image change detection techniques. *Remote Sensing of Environment* 160 (April):1–14. doi: 10.1016/j.rse.2015.01.006.

Wang, D., J. Gong, L. Chen, L. Zhang, Y. Song, and Y. Yue. 2012. Spatio-temporal pattern analysis of land use/cover change trajectories in Xihe watershed. *International Journal of Applied Earth Observation and Geoinformation* 14 (1):12–21. doi: 10.1016/j.jag.2011.08.007.

Warrens, M. J. 2015. Relative quantity and allocation disagreement measures for category-level accuracy assessment. *International Journal of Remote Sensing* 36 (23): 5959–69. doi: 10.1080/01431161.2015.1110265.

Zaiss, R. 2014. *Project NumeriSud SPHAERA-GEO, géoréférencement et mosaïquage des cartes de l'IRD* [NumeriSud Project SPHAERA-GEO, georeferencing and mosaicking of IRD maps]. Bondy, France: Institut de recherche pour le développement.

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Appendix: Python Code Using OpenCV Library to Reduce Noise in Image

```
import cv2


img = cv2.imread('noisy.png')
new_img = img
filename = ''


for x in range(100):
  new_img = cv2.fastNlMeansDenoisingColored(img,None,x,10,7,21)
  filename = "output/denoised_h_value_" + str(x) + ".png"
  cv2.imwrite(filename, new_img)
    print("Saved ", filename)
```

We use a “for” loop to iterate through different filter strengths to compare different outputs.