A generalized computer vision approach to mapping crop fields in heterogeneous agricultural landscapes

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Smallholder farms dominate in many parts of the world, particularly Sub-Saharan Africa. These systems are characterized by small, heterogeneous, and often indistinct field patterns, requiring a specialized methodology to map agricultural land cover. Using a variety of sites in South Africa, we present a new approach to mapping agricultural fields, based on efficient extraction of a vast set of simple, highly correlated, and interdependent features, followed by a random forest classifier. We achieved similar high performance across agricultural types, including the spectrally indistinct smallholder fields as well as the more easily distinguishable commercial fields, and demonstrated the ability to generalize performance across large geographic areas. In sensitivity analyses, we determined multi-temporal information provided greater gains in accuracy than multi-spectral information.

Keywords: land cover, agriculture, Sub-Saharan Africa, computer vision, machine learning

1. Introduction

Improving the capacity to monitor the spatial distribution of agriculture, particularly among smallholder farmers, is critical to increasing agricultural productivity and food security in many parts of the world. Smallholder agriculture, which dominates in Sub-Saharan Africa and other world regions, features rainfed production for household consumption and use of family labor and minimal technology \[1-4\]. These systems are also characterized by small, heterogeneous, and often indistinct field patterns \[5-8\]. The prevalence of smallholder farms highlights the need for a specialized methodology to monitor agriculture across farming types, including both smallholder and commercial.

Of the regions where smallholder agriculture dominates, Sub-Saharan Africa is the most important, due to its geographic size and status as a potential center of agricultural growth in the coming decades. Of all farms in Sub-Saharan Africa, 80% are less than 2 hectares and the mean farm size of 1.6 hectares is significantly smaller than most world regions (Table 1) \[1\] [9-13]. Increasing agricultural productivity is crucial in Sub-Saharan Africa, because its population is expected to double by 2050 \[14\]. The population remains predominantly rural despite recent urbanization \[15\], and 60% of the workforce is employed in agriculture.

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Population growth drives down field sizes and pushes farmers onto marginal lands. As a result, growing climate variability, characterized by less frequent and more intense rain events, increases farmers’ vulnerability to food insecurity [15, 17–22]. As smallholder field sizes decrease, large-scale international land acquisitions and government-sponsored agricultural growth corridors promote consolidation of remaining farmland into commercial enterprises [4, 23–27]. Efforts to monitor agricultural change on the ground are confounded by a widespread shortage of agricultural data in Sub-Saharan Africa, in part due to limited government capacity [9, 21, 28–30]. Therefore, an accurate accounting of agricultural land cover, across both smallholder and commercial farming, is needed to track and promote food security in Sub-Saharan Africa.

<table>
<thead>
<tr>
<th>World region</th>
<th>Average farm size (hectares)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Africa</td>
<td>1.6</td>
</tr>
<tr>
<td>Asia</td>
<td>1.6</td>
</tr>
<tr>
<td>Western Europe</td>
<td>27.0</td>
</tr>
<tr>
<td>Latin America and Caribbean</td>
<td>67.0</td>
</tr>
<tr>
<td>North America</td>
<td>121.0</td>
</tr>
</tbody>
</table>

Table 1: Estimated farm sizes of selected world regions [11, 13]

In data-sparse regions, remote sensing satellite imagery provides alternative means to monitor agriculture. However, land cover data sets derived from remote sensing contain large uncertainties regarding the total area as well as the spatial distribution of agriculture [5–8, 31, 32]. Moreover, readily available remote sensing data sets, such as MODIS (250 m) and Landsat (30 m), lack sufficient spatial resolution to study smallholder fields, which are often smaller than 1 hectare (100 m x 100 m) [6, 8, 33]. For example, a previous study using Landsat imagery to identify agricultural fields in the United States struggled with small, irregular fields of less than 1.5 hectares, though these conditions represented only a minority of studied fields [34].

High-resolution satellite imagery (≤ 2 m) provides the necessary detail to observe smallholder agriculture and is becoming increasingly available and affordable [6, 8, 33, 35, 36]. As coverage improves, automated classification algorithms are used to extract actionable data from images. Prior efforts to automatically classify agricultural fields using high-resolution imagery have struggled due to (1) the nature and appearance of smallholder agriculture, (2) the properties of high-resolution imagery itself, and (3) the design of classification algorithms.

First, the high spatial variability in land cover poses a classification challenge, particularly among smallholder agricultural fields, which are small and irregularly shaped [37]. Smallholder fields are less visually defined, exhibiting indistinct boundaries between neighboring fields as well as ambiguity between fields and natural vegetation [5, 8]. They also exhibit more variability in spectral and phenological signatures, due to rainfed farming, sub-optimal management, low cropping intensity, fallowing, abandonment, and the inclusion of large trees within fields [31, 33, 38, 39] (Figure 1). Thus, these conditions highlight the need for a specialized methodology for smallholder agriculture.

Second, the level of detail increases in high-resolution imagery, which raw spectral values or simple features are inadequate to describe. In high-resolution imagery, land cover classes
Figure 1: Examples of false color (NIR1, red, green) images of smallholder (a, b) and commercial (c, d) agriculture in Sub-Saharan Africa, highlighting the highly variable spectral characteristics of smallholder agriculture (500 x 500 2 m pixel subsets).

have lower spectral inter-class variability and higher intra-class variability, creating ambiguities in classification [40–42]. Variability also increases as images are mosaiced together, necessitated by lower collection frequency of high-resolution imagery [8, 35]. Previous efforts to handle increased detail in high-resolution imagery have focused on expanding the feature space by manually handcrafting higher order features suitable to a specific application. Features that capture textural and contextual information (e.g. grey-level co-occurrence matrices (GLCM), filter bank responses, and textons) have been found to improve classification accuracy over spectral information alone, but their use has been limited by their complexity and high computational cost [40–50]. Incorporating additional multi-spectral bands in features, either as raw inputs or calculated image transformations like vegetation indices, may also increase accuracy, but without selection of the most discriminative bands, this approach is limited by high band correlation [40, 51, 52]. Multi-temporal imagery has also been found to increase accuracy, especially for agriculture, by capturing details on phenological profiles and filling in missing data [40, 53–56]. Overall, extracting more features derives greater information from high-resolution imagery. However, classification algorithms struggle with the expanded feature space, necessitating the use of feature selection to determine the most useful ones, often in a separate stage prior to classification [40, 57, 58].

Third, a classification algorithm must efficiently handle the vast features spaces of highly correlated and interdependent features required to adequately describe smallholder agriculture in high-resolution imagery [10, 57, 58]. An algorithm must also resist overfitting to training data and have high generalization performance to classify large expanses of new imagery [59]. Previous efforts have found that tracking land cover changes over time lends itself to a supervised classification approach, in which a classifier is initially trained to identify prescribed classes with labeled data and then repeatedly deployed on a time series of images [60]. Yet supervised classification of remote sensing imagery is often deemed a local approach for small areas, with a reputation of being difficult to repeat over large areas [39]. Within supervised classification, non-parametric classifiers are increasingly preferred, due to their ability handle extremely large feature spaces and data sets, robustness to outliers and noise, and outperformance of parametric classifiers in complex landscapes [35, 10, 60, 68]. Furthermore, classifiers with probabilistic output, as opposed to hard classifications, are gaining popularity in remote sensing for highlighting the spatial variation in classification.
quality and confidence, which is crucial for utilizing classification results in decision making \cite{40, 60, 69}. Probabilistic output can also be post-processed in a variety of ways, ranging from simple thresholding for obtaining hard classifications to image segmentation and object detection.

This study develops a methodology to differentiate heterogeneous agricultural land cover in high-resolution imagery of Sub-Saharan Africa that is effective across a range of agricultural types, including the small, irregular fields of the dominant smallholder class. In a supervised classification approach, we utilize techniques from computer vision and machine learning, two fields that are increasingly used in remote sensing analyses as high-resolution imagery becomes readily available. Computer vision provides the means to detect, recognize, and track complex objects in images, while machine learning enables assimilation of vast quantities of data \cite{70}, a powerful combination for deriving actionable data from high-resolution imagery that generalizes across large areas.

First, to address the problems of adequately describing the small, irregular fields of smallholder agriculture and handling the great level of detail in high-resolution imagery, we efficiently extract a unique set of many simple, highly correlated, and interdependent features. Second, we utilize a supervised, non-parametric machine learning classifier to handle the vast feature space and provide probabilistic output of the likelihood that pixels belong to agricultural fields. We assess our classification accuracy using the metrics of receiver operating characteristic (ROC) curves and the area under the curve (AUC), finding similar high performance (AUC > 0.90) across agriculture types, including smallholders. We also investigate the relative roles of multi-temporal and multi-spectral information, given the data limitations of high-resolution satellite imagery in Sub-Saharan Africa, and find that multi-temporal imagery contributes to greater gains in accuracy. Finally, we propose further work to post-process the probabilistic output into maps of individual agricultural fields.

2. Data

2.1. Study area

South Africa was selected as our study area, due to greater coverage of high-resolution imagery than other areas of Sub-Saharan Africa, as well as availability of official government-sponsored agricultural land cover maps \cite{71}. South Africa also has a large, diverse agricultural sector, ranging from smallholder farming to commercial enterprises, enabling us to test the generalizability of our algorithm across various landscapes and farming types. Eight study sites were selected with a mix of smallholder rainfed subsistence, rainfed commercial, and center pivot irrigated fields in the primary agricultural regions of the country, based on availability of imagery (Figure \ref{fig:study_area}).

2.2. Satellite imagery

For this study, we acquired DigitalGlobe Worldview-2 imagery, which typifies the spatial resolution of future sensors and provides a good compromise between cost, resolution (spatial, spectral, and temporal), and geographic coverage for current applications. For each site, we obtained pairs of orthorectified images, each 25 km$^2$, which include a growing season image (December-April) and an off season image (July-November) within the same year or one year.
apart. Each image contains a panchromatic band at 0.5 meter resolution (aggregated using mean values to 2 meter resolution) and 8 multi-spectral bands at 2 meter resolution.

3. Methodology

3.1. Overview

We frame our agricultural field classification task as a supervised binary classification problem to determine the unknown class $y$ of pixels as either field or non-field. In supervised classification, a classifier is initially trained with labelled data and then deployed on previously unseen data. Specifically, using an input feature vector, $x$, extracted from a pixel of interest, a trained classifier determines the posterior class probability of the pixel, $P(y|x)$, expressed as the likelihood of the pixel belonging to a field.

We define agriculture as fields that have been recently active. This approach is preferred over classifying currently active fields, due to the frequent fallowing and rotation of fields, variety of planted crops, and range of planting dates that is characteristic of Sub-Saharan Africa agriculture. Fields that are obviously grown over and abandoned are labelled as non-field areas. Given the complex, small-scale nature of Sub-Saharan African agriculture, some disagreement in labeling is expected. As is the case with most machine learning algorithms, we expect the volume and variety of training data to enable the algorithm to handle some level of noise.

3.2. Hand-digitization of labelled data

To supply labelled data for supervised classification, each agricultural field was hand-digitized [72] and additional metadata on agricultural type (rainfed subsistence, rainfed commercial, or center pivot) was stored. The hand-digitization was performed in QGIS [72], using the 2 meter resolution data as well as the panchromatic band at the original 0.5 meter resolution for reference. Hand-digitized field boundaries were also cross-referenced with official agricultural land cover maps from the South African government to increase ground-truth accuracy. Hand-digitization of entire fields was preferred over classifying randomly selected points, because it provided a wider variety of examples in each class that captured
Figure 3: Example of Worldview-2 imagery (a) and hand-digitized field boundaries (b).

within-field spectral variability. The resulting field boundaries were then rasterized into labeled images to be included in the training data (Figure 3).

3.3. Feature extraction

We overcame the problems of manual feature design and selection by extracting a comprehensive set of over 15,000 simple, highly correlated, and interdependent features, using an expanded version of the Randomized Quasi-Exhaustive (RQE) feature approach [41, 42]. These features were an alternative to calculating specific features tailored to one data set, increasing the generalization performance of the algorithm.

The features were computed efficiently based on integral images, a pioneering image representation from computer graphics and computer vision [73, 74]. Integral images, also called summed area tables, are both a data structure and an algorithm, enabling fast, efficient calculation of the sum of values in a rectangular subset of an image, which forms the basis of each of the calculated features. An image is pre-processed into a summed area table in which a pixel, $s$, is defined as the sum of all original image pixels, $i$, that are located above and to the left:

$$ s_{\sum}(x, y) = \sum_{x' \leq x, y' \leq y} i(x', y') $$

(1)

Each pixel in the summed area table can be efficiently calculated in a single pass using image pixels and previously calculated values, thus building up the table beginning in the top left corner:

$$ s(x, y) = i(x, y) + s(x - 1, y) + s(x, y - 1) - s(x - 1, y - 1) $$

(2)

Therefore, the sum of any rectangular region of the image can be computed in constant time, using the four pixels of the summed area table that define the corners of the rectangle.
(top left: A, top right: B, bottom left: C, and bottom right: D):

\[ \sum_{x_0 < x \leq x_1, y_0 < y \leq y_1} i(x, y) = s(D) + s(A) - s(B) - s(C) \]  

(3)

Using integral images, the features were generated within a sliding window, or small image patch surrounding the pixel of interest, thereby extracting contextual and textural data and acting as an intermediate between pixel-based and object-based classification [41, 42, 50, 75]. A sliding window of 5 x 5 pixels provided the best performance for our application. The features were extracted in an identical process for each pixel of interest by applying a set of feature types to a set of feature channels.

3.3.1. Feature channels

To extract features, we first constructed a stack of feature channels, consisting of the original imagery bands and several intermediate image products that drew additional information from the image pairs (Table 2).

The first group of intermediate image products were calculated with mathematical morphological operations, which “simplify image data preserving their essential shape characteristics and eliminating irrelevancies” [76]. We applied morphological image transformations at two scales to smooth natural vegetation and highlight structural information in the image [77]. We used a series of basic morphological operators, including erosion, dilation, opening, and closing. We also use filtering by reconstruction, which has been shown to better preserve shapes in the original image [78].

The second group of intermediate imagery products consisted of probability maps of where circular objects are likely to occur, which highlighted center pivot agriculture. Without these added feature channels, center pivot agriculture can complicate classification, due to differences in the phenologies of irrigated and rainfed crops. The probability maps were calculated by passing a simple circle detector, a common tool in computer vision, over the imagery and ranking potential circles based on the metric of circle strength.

After combining the original image bands and the intermediate image products, mean filtering was applied to each channel. Mean filtering smoothed and removed noise from the images by replacing each pixel with the mean of surrounding pixel values within a sliding window without suffering a significant loss of detail at the selected window sizes of 3 x 3 and 5 x 5 pixels. Thus, with the addition of the intermediate image products and mean filtering, the training data set expanded from the original nine imagery bands to 72 feature channels.

3.3.2. Feature types

We defined a range of feature types, which served as templates for extracting features from the feature channels for a pixel of interest. The feature types, described in Table 3, were calculated based on the pixel values or the mean value of a patch of pixels within a sliding window centered around a pixel of interest.

The feature types increase in complexity, yet remain efficient to calculate using integral images. Within a single feature channel, the first feature type (Table 3A.1) extracted every pixel value within the sliding window, the second (Table 3A.2) calculated the mean value of
a patch around the pixel of interest, and the third (Table 3A.3) compared the mean values of patches of differing sizes around the pixel of interest.

The next group of feature types utilized comprehensive pairs of feature channels to increase descriptive power. To compare the mean values of a patch in two feature channels, the first feature type (Table 3B.1) took the difference, while the second (Table 3B.2) introduced a nonlinear comparison similar to the calculation of the normalized difference vegetation index (NDVI).

To more efficiently describe a wider range of textures and extract positional information, an additional feature type (Table 3C.1) included randomized elements. A patch of randomized size and position was selected within the sliding window, mirrored over the central pixel of interest, and the difference was calculated between the mean pixel value of the two patches. We calculated 500 of these randomized features for each pixel of interest.
<table>
<thead>
<tr>
<th>Feature channel</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Satellite imagery</strong></td>
<td></td>
</tr>
<tr>
<td>Growing &amp; off season images</td>
<td><img src="image1.png" alt="Example" /> <img src="image2.png" alt="Example" /></td>
</tr>
<tr>
<td>(8 multi-spectral &amp; 1 panchromatic bands)</td>
<td></td>
</tr>
<tr>
<td>18 channels</td>
<td></td>
</tr>
<tr>
<td><strong>Intermediate image products</strong></td>
<td></td>
</tr>
<tr>
<td>Two morphological image transformations on panchromatic bands</td>
<td><img src="image3.png" alt="Example" /> <img src="image4.png" alt="Example" /></td>
</tr>
<tr>
<td>4 channels</td>
<td></td>
</tr>
<tr>
<td>Circle detection in growing &amp; off season images</td>
<td><img src="image5.png" alt="Example" /> <img src="image6.png" alt="Example" /></td>
</tr>
<tr>
<td>2 channels</td>
<td></td>
</tr>
<tr>
<td><strong>Mean filtering</strong></td>
<td></td>
</tr>
<tr>
<td>3x3 and 5x5 mean filtering on all channels</td>
<td><img src="image7.png" alt="Example" /> <img src="image8.png" alt="Example" /></td>
</tr>
<tr>
<td>48 channels</td>
<td></td>
</tr>
<tr>
<td><strong>Total channels = 72</strong></td>
<td></td>
</tr>
</tbody>
</table>

Table 2: Descriptions of features channels. A set of feature types was applied to this set of feature channels during feature extraction.
<table>
<thead>
<tr>
<th>Feature type</th>
<th>Example</th>
</tr>
</thead>
</table>
| **A.1:** Every pixel value within sliding window in a feature channel  
\(x_{1,1}, x_{1,2}, \ldots, x_{1,n-1}, x_{1,n}\) | ![Pixel of interest in sliding window](Image)  
\(\rightarrow \begin{array}{c} x_{1,1} \\ \vdots \\ x_{1,n} \end{array} \) |
| **A.2:** Mean of square within sliding window in a feature channel \(\bar{x}_1\) | ![Pixel of interest in sliding window](Image) |
| **A.3:** Difference of means of two squares (different size) in a feature channel \(\bar{x}_1 - \bar{x}_2\) | ![Pixel of interest in sliding window](Image) |
| **B.1:** Differences of means of two squares (same size) between two feature channels \(\bar{x}_1 - \bar{x}_2\) | ![Pixel of interest in sliding window](Image)  
\(\text{Channel } c_1\)  
\(\text{Channel } c_2\) |
| **B.2:** Simulated NDVI of two squares (same size) between two feature channels  
\(\frac{\bar{x}_1 - \bar{x}_2}{\bar{x}_1 + \bar{x}_2}\) | ![Pixel of interest in sliding window](Image)  
\(\text{Channel } c_1\)  
\(\text{Channel } c_2\) |
| **C.1:** Difference of means of two rectangles (same random size) symmetrically mirrored in a feature channel \(\bar{x}_1 - \bar{x}_2\) | ![Pixel of interest in sliding window](Image)  
\(\text{Channel } c_1\) |

Table 3: Descriptions of feature types that were applied to the set of feature channels during feature extraction.
3.4. Classifier selection

We used a random forest classifier from the field of machine learning, trained on the class labels from the hand-digitized field boundaries and the extracted feature vectors for the pixels in the training data set, to output the posterior probability of each pixel belonging to an agricultural field. The algorithm is a custom implementation of the random forest classifier that is fully parallelized and optimized for extracting and handling features from imagery. The algorithm code was written in Matlab/C++ and based on the work of Schroff et al. [79] and Tokarczyk et al. [41, 42].

Originally developed by L. Breiman in 2001 [80], a random forest is a collection of decision trees, each trained on a random subset of the training data, which allows for full parallelization of the algorithm. Each decision tree is composed of nodes, which perform binary splits on the training data based on a threshold value for a selected feature, and pass the training data to the next level of nodes. Each node is constructed by evaluating a random subset of features to maximize information gain. As the training data passes through the decision tree, it results in a pixel classification at the terminal node. Results are averaged across the trees to obtain a posterior class probability for the pixel. The two main sources of random behavior, random subsets of data for training individual trees and random subsets of features for node selection, increase generalization performance by creating independent decision trees that do not overfit to the training data set [50, 75, 81, 82].

Variations of the random forest algorithm achieved the highest accuracy in an evaluation of 179 classifiers on 121 commonly used machine learning benchmarking data sets [83]. Random forests are also gaining popularity outside the machine learning community, particularly in the natural sciences, because the algorithm excels in handling complex, nonlinear, high dimensional data sets [84, 85]. Random forests have been used in a variety of applications, including ecological modeling [84, 86, 87], global tropical forest carbon mapping [59, 88], classification of geologic surfaces for space exploration missions [75, 82], and medical image processing [89]. They are also increasingly used for remote sensing land cover classification [33, 38, 59, 65, 66, 68, 90–94], including those using high-resolution imagery [35, 67].

Several parameters of the random forest classifier were optimized for our application. Each tree in the random forest was trained using a different random selection of 5,000,000 training data points (about 12%), split evenly between field and non-field pixels, which was determined to be sufficient due to the high correlation between neighboring pixels. During the training phase, 100 trees were grown with a maximum tree depth of 10 levels of nodes.

3.5. Cross-validation scheme

To assess the algorithm’s accuracy, we used an image-based, leave-one-out (LOO) cross-validation scheme, in which training data was drawn from seven of the eight images and the remaining image was used for testing, rotating through all combinations. This cross-validation approach ensured that the algorithm only classified previously unseen data and that highly correlated pixels within an image were not divided between training and test sets, which could inflate accuracy performance.

Other cross-validation approaches that are based on pixels instead of images, such as randomly splitting pixels into training and testing sets, dividing an image into training and testing regions, or the “out-of-bag” validation scheme built into random forests, may cause the algorithm to overfit to the data set and produce erroneously high accuracy scores.
due to the high spatial correlation within images [60, 95]. Our cross-validation approach also simulated classifying a new image based on a curated database of hand-digitized field boundaries for future, large-scale deployments of the algorithm.

### 3.6. Error/accuracy metrics

To assess accuracy, we used a common metric for binary classification in computer vision and machine learning: the receiver operating characteristic (ROC) curve. The ROC curve compares the rates of true positives and false positives in a binary classification task. The curve yields a single metric suitable for comparison: the area under the curve (AUC). For reference, AUC values of 1.0 correspond to perfect discrimination, while models with AUC values of less than 0.5 are considered to have no predictive capability. An AUC value of 0.7 is usually determined as the threshold for usefulness in an application, while scores greater than 0.9 denote high performance and are the most useful for classification [96].

Metrics were calculated on a per-image basis, as opposed to a per-pixel basis, to assess generalization performance as the algorithm is deployed on previously unseen satellite images, which may vary widely in appearance. To provide further detail on the binary classification accuracy, the pixels belonging to agricultural fields in each image were divided into 3 subclasses (rainfed subsistence, rainfed commercial, and center pivot) and ROC curves were calculated for each.

### 3.7. Experiments

We carried out a series of experiments to evaluate the algorithm’s performance under varying conditions of data availability, recognizing that Sub-Saharan Africa does not yet have the same remote sensing coverage as other regions of the world. Specifically, we investigated the relative importance of temporal versus spectral depth.

- **Primary analysis:** We evaluated the algorithm’s performance using all available images (growing season and off season images) and image bands (panchromatic and 8 multi-spectral bands).

- **Sensitivity analysis with multi-temporal images:** While continuing to use all multi-spectral bands, we retrained the algorithm using:
  - Growing season images only
  - Off season images only

- **Sensitivity analysis with multi-spectral bands:** While continuing to use both multi-temporal images, we retrained the algorithm using the following combinations of multi-spectral bands:
  - Panchromatic and red-green-blue (RGB)
  - Panchromatic, RGB, and the first near-infrared band (NIR1)
4. Results

4.1. Primary analysis

In the primary analysis, where the algorithm was trained using both growing season and off season images and all multi-spectral image bands, the mean AUC value across images (n=8) was 0.91 ± 0.02 (Figure 4). For individual agricultural sub-classes, mean AUC values were greater than 0.90 for center pivot, rainfed commercial, and rainfed subsistence, signifying high performance (Figure 5).

Figure 4: Receiver operating characteristic (ROC) curves for each image (n = 8, M = 0.91, SE = 0.02). Classifiers were trained on both growing season and off season images and all image multi-spectral bands in a leave-one-out cross-validation scheme (trained on 7 images and tested on remaining 1 image).
Figure 5: Mean and standard error of AUC values of each agricultural sub-class across images: center pivot (M = 0.93, SE = 0.04), rainfed commercial (M = 0.92, SE = 0.03), and rainfed subsistence (M = 0.90, SE = 0.02).

In addition to overall accuracy, the algorithm’s output was assessed qualitatively by examining how well areas of high probability of belonging to an agricultural field corresponded to hand-digitized fields. We aimed to achieve not only high overall accuracy, but also show coherent regions of similar posterior probability corresponding to fields, which are important for further work on segmentation of individual fields.

Figure 6 depicts examples of the algorithm’s performance. Fields vary in appearance (color, texture, brightness, vegetation type, phenology) between the examples, yet generally correspond to areas of increased probability of belonging to a field over background pixels in Figures 6a - 6c. Figure 6a shows discretization between individual smallholder fields and accurately distinguishes between uncultivated or abandoned fields and active fields with a high degree of confidence. Figure 6b depicts differentiation of smallholder fields, though they contain trees and shrubs, from natural background vegetation. Figure 6c displays differentiation of commercial agriculture, both rainfed and center pivot, from background vegetation into cohesive regions of similar confidence, regardless of the fact that the half of the center pivot has the opposite growing season of the rainfed fields. Figure 6d, however, depicts a case of lower algorithm performance, in which degraded soil areas and abandoned fields are assigned similar posterior probability values as pixels within active fields.
Figure 6: Examples of algorithm’s performance in image subsets of 250 x 250 pixels (2 m). From left to right, the columns display the growing season and off season satellite images, the hand-digitized field boundaries, and the classifier output of the posterior probability that pixels belong to an agricultural field.
4.2. Sensitivity analyses: Importance of multi-temporal images and multi-spectral bands

Training the classifier with multi-temporal imagery (both growing season and off season images) increased accuracy and decreased standard error, compared to training with a single image (Figure 7a). However, training the classifier with an increasing number of multi-spectral bands had little effect on the mean accuracy or standard error of the classifier (Figure 7b).

For individual agricultural sub-classes (Figure 8), rainfed types of agriculture, both commercial and subsistence, responded more positively to training with multi-temporal imagery than center pivot irrigated agriculture, as shown by increasing accuracy and decreasing standard error (Figure 8a). However, center pivot agriculture showed a slight increase in accuracy when trained with all multi-spectral bands (Figure 8b).
Figure 7: Mean and standard error of AUC values across images (n=8) for (a) multi-temporal sensitivity analysis, which trained the algorithm by varying the number of images per site, but using all multi-spectral bands: Off-season image (M = 0.87, SE = 0.03), growing season image (M = 0.88, SE = 0.03), and both images (M = 0.91, SE = 0.03); and (b) multi-spectral sensitivity analysis, which trained the algorithm by varying the number of multi-spectral bands, but using both images: Pan + RGB (M = 0.90, SE = 0.02), Pan + RGB + NIR1 (M = 0.90, SE = 0.02), and all bands (M = 0.91, SE = 0.02).
Figure 8: Mean and standard error of AUC values of each agricultural sub-class across images (n=8) for: (a) multi-temporal sensitivity analysis, which trained the algorithm by varying the number of images per site, but using all 9 multi-spectral bands; and (b) multi-spectral sensitivity analysis, which trained the algorithm by varying the number of multi-spectral bands, but using both images (growing season and off season).
5. Discussion and conclusions

We have presented here a new approach to mapping agricultural fields, based on efficient extraction of a vast set of features followed by a random forest classifier. The generalizability of this approach is demonstrated by high and comparable accuracy across spectrally indistinct smallholder fields and more easily distinguishable commercial fields.

In our primary analysis using multi-temporal imagery (growing season and off season images) and all multi-spectral bands, our algorithm achieved similar high performance (AUC > 0.90) across agricultural types. These results are consistent with the hypothesis that the set of features was capable of capturing subtle textural and contextual details, enabling the classifier to perform well in difficult cases of smallholder agriculture, such as small, irregular rainfed fields with indistinct boundaries and low differentiation between cultivated areas, abandoned fields, and natural vegetation. Incorporating circle detection in the features also allowed center pivot irrigated fields to be accurately classified, despite some fields having a growing season opposite of rainfed fields.

Our findings related to expanded feature spaces are supported by the work of Mukashema et al. [97], who found that spectral variables alone could not adequately distinguish Rwandan coffee fields in high resolution imagery, which also exhibit similarly high variability. The authors increased classification accuracy by extracting features from ancillary data, including a digital elevation map (DEM) and a forest map. Expanded feature spaces were further explore in Hayes et al. [35], who overcame low spectral resolution (red, blue, green, and NIR bands) by using a random forest classifier and features extracted from high resolution imagery and ancillary data to map agricultural fields in the United States. In comparison to the smallholder fields in our study area, the U.S. fields were more spectrally and geometrically distinct, necessitating only one texture measure and one NDVI feature channel to achieve the required accuracy.

In sensitivity analyses, we determined that multi-temporal imagery increased accuracy more than additional multi-spectral bands, particularly for the rainfed subsistence and rainfed commercial sub-classes. These results suggest that seasonal changes in texture and patterns are more descriptive than the spectral signatures themselves, which can be highly variable within the dominant smallholder class. Moreover, multi-temporal data reduced variability in the results, as evidenced by decreased standard error in mean classification accuracy.

Similar to our results, Low et al. [98] found that several multi-temporal images generally resulted in higher accuracy and lower uncertainty for high-resolution classification of Central Asian irrigated agriculture compared to single date images. Also, Yan and Roy [34] employed multiple years of weekly Landsat data to extract crop fields in the United States, highlighting the ability of multi-temporal data to handle the problems of crop rotations and inter-annual variability, which are also relevant to Sub-Saharan African agriculture.

As temporal resolution of hyperspatial imagery increases in Sub-Saharan Africa, future work can explore whether a single pair of growing season and off season images captures the most crucial temporal patterns in the simplest form for the classifier, or if the use of expanded time series of images is warranted. Additional multi-temporal imagery could highlight more subtle seasonal pattern changes that would help differentiate between cultivated fields and abandoned fields or degraded soils. These cases had lower accuracy than differentiating
between cultivated fields and natural vegetation, due to similarity of visual patterns. Finer
temporal resolution could also improve accuracy in cases where the temporal gap in image
pairs created disagreement (e.g. a cultivated field in the growing season image was unplowed
natural vegetation in the off season image), resulting in lower accuracy. Furthermore, the
lack of discriminative power of multi-spectral bands, in comparison to multi-temporal data,
supports the current revolution in small, low cost satellites. These “nanosats”, pioneered by
such companies as Planet Labs and Skybox, place greater emphasis on timely, high-resolution
imaging, as opposed to greater spectral depth.

As shown in Figure 6, the classification algorithm produced coherent areas of similar pos-
terior probability, which are critical for further post-processing to extract individual fields
as well as assessing the confidence of the output for decision making applications. A study
by Ozdarici-Ok et al. [99] achieved promising results in segmenting individual agricultural
fields in high-resolution images of Turkey, using global conditional random field (CRF) label-
ing with graph cuts, a segmentation technique from image processing and computer vision
that smooths the posterior class probabilities from a classifier [100, 101]. Though most of
the studied fields were clearly defined, rectangular in shape, and single-cropped, their ap-
proach could be expanded to include larger feature spaces that are crucial for distinguishing
smallholder agriculture in Sub-Saharan Africa.

Overall, our algorithm provides a flexible framework that can be expanded to accom-
modate increases in temporal and spectral resolution of data with minimal effort. The
parallelized structure of the random forest can handle the expanding feature space as well
as the addition of more training data ad infinitum, theoretically limited only by the avail-
ability of computing resources. To maximize efficiency, future algorithm development will
focus on optimizing training data using a combination of crowd-sourcing and active learning
[102, 104]. This approach would interactively select the most informative training images
based on image similarity metrics and changes in algorithm accuracy, which would then be
submitted to users of crowd-sourcing engines for hand-digitization of field boundaries [8]. As
opposed to random assignment of images to users, our goal is to determine the minimum
training data set needed to maximize algorithm accuracy as well as select new images to
expand the geographic range of our algorithm.

Finally, our approach has shown the ability to generalize well across large areas and dis-
parate agricultural land cover types, paving the way for its large-scale deployment in which
new images are classified using a curated database of hand-digitized field boundaries. In ad-
dition to providing high-resolution maps of agricultural land cover and reducing uncertainties
in existing data sets, applying this algorithm over Sub-Saharan Africa can provide a critical
and improved constraint for regional crop productivity [105, 106] and agro-climatological
assessments [107], as well as assessments of land cover change.

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References


24


