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Crop area estimation using high and medium resolution satellite imagery in areas with complex topography

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[1] Reliable estimates of cropped area (CA) in developing countries with chronic food shortages are essential for emergency relief and the design of appropriate market-based food security programs. Satellite interpretation of CA is an effective alternative to extensive and costly field surveys, which fail to represent the spatial heterogeneity at the country-level. Bias-corrected, texture based classifications show little deviation from actual crop inventories, when estimates derived from aerial photographs or field measurements are used to remove systematic errors in medium resolution estimates. In this paper, we demonstrate a hybrid high-medium resolution technique for Central Ethiopia that combines spatially limited unbiased estimates from IKONOS images, with spatially extensive Landsat ETM+ interpretations, land-cover, and SRTM-based topography. Logistic regression is used to derive the probability of a location being crop. These individual points are then aggregated to produce regional estimates of CA. District-level analysis of Landsat based estimates showed CA totals which supported the estimates of the Bureau of Agriculture and Rural Development. Continued work will evaluate the technique in other parts of Africa, while segmentation algorithms will be evaluated, in order to automate classification of medium resolution imagery for routine CA estimation in the future.

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1. Introduction

[2] In 2001–2003, the Food and Agriculture Organization (FAO) estimates that 820 million people were undernourished in developing countries [*FAO*, 2006b]. Contrary to other regional trends, sub-Saharan Africa has seen a significant increase in undernourishment from 169 million people in 1990–1992 to 206 million people in 2001–2003, representing one-fourth of people suffering chronic hunger worldwide. Due primarily to economic growth and significant expansions of per capita food production, Ethiopia has achieved a significant reduction in the number of undernourished (17% from 1993–1995 to 2001–2003). Even so, 15 million Ethiopians face chronic or transitory food insecurity, with up to 10% of the population facing food shortages in years of above-average productivity [*FAO*, 2006a].

[3] In the past several decades, more proactive and preventative market oriented strategies for combating food insecurity in sub-Saharan Africa have gradually replaced direct food aid, the latter of which is now restricted to emergency relief [*Christensen*, 2000; *Clay*, 2003]. Market oriented strategies, such as donor export incentives, employment generation, and work-based food aid, aim to stimulate economic growth, trade, and agricultural productivity.

[4] Food production, an important indicator of food security, is the product of the amount of area being cropped and the yield per cropped area. Cropped area (CA) is a function of many inputs, including land tenure policy, rainfall forecasts, and farmer incentives (market forces and government subsidies). Despite the early successes of the Large Area Crop Inventory Experiment (LACIE) [*Hammond*, 1975; *MacDonald et al.*, 1975, 1980] and the Agriculture and Resources Inventory through Aerospace Remote Sensing [*Hixson et al.*, 1981a, 1981b], food production estimates for many developing African nations still face significant uncertainty. While simple models of crop water scarcity [*Senay and Verdin*, 2001; *Verdin and Klaver*, 2002] tend to track well with yield anomalies in rainfed semi-arid regions of Africa, the CA term of the production equation is still poorly specified. It is therefore imperative for effective food security initiatives, as well as early warning and import planning, that reliable estimates of CA are made.

[5] Several techniques have been adapted for crop estimation using aerial photographs and satellite images, including: pixel count [*Bauer et al.*, 1978; *Fang*, 1998; *Shao et al.*, 2001; *Sridhar et al.*, 1994], supervised classification [*Gallego and Rueda*, 1993], Bayesian/fuzzy classification and spectral un-mixing [*Gorte and Stein*, 1998; *Quarmby et al.*, 1992], and area frame sampling

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[*Gallego*, 1999; *Pradhan*, 2001]. Pixel count is dependent on classification accuracy, which is limited by the presence of mixed pixels, colocation inaccuracy, and the spatial correlation between training sites and test sites. Furthermore, classification techniques and spectral un-mixing are highly sensitive to the variance among categories and correlation between spectral bands. The presence of mixed pixels induces significant errors, particularly in developing countries, where small subsistence farms adjoin uncultivated areas [*Ozdogan and Woodcock*, 2006]. Location and interpretation error are limitations of area frame sampling as well, however several applications involving unbiased estimators (ground survey or high resolution aerial photos), show little deviation from actual crop inventories [*Gallego*, 2004].

[6] The area frame sampling approach has been applied in a number of ways in agricultural surveys. The general principle involves a multistage sampling approach where the scale of segments, or sampling units, at each stage is different from other stages. Statistical relationships between the high and medium resolution data are then used to estimate the CA for the largest unit practical. An example of a number of surveys performed for various countries with different stage sampling units was produced by *FAO* [1998]. In these studies, the segments were political districts, crop reporting districts, arbitrary areas on a satellite image, a single farm, or a household. The area frame approach can be structured to take advantage of available resources to maximize the amount of information going into the final statistical estimate. In areas where the execution and monitoring of ground surveys is difficult or the area of study is large, the use of remotely sensed image segments has a substantial economic advantage. As a result, several national/regional organizations use area frame sampling to estimate CA in Europe and the United States, including: the USDA Foreign Agriculture Service, Statistics Canada, European Union Monitoring Agriculture with Remote Sensing Project, and the Italian AGRIT project. Results of a study in Hamadan Province, Iran are promising for developing countries, as area frame sampling using aerial photos showed an overall accuracy of 99.8% estimation of annual crop inventories [*Pradhan*, 2001].

[7] This research developed a hybrid high-medium resolution technique to determine CA for major crop producing zones in Ethiopia during the 2005 primary growing season that combines spatially limited, unbiased estimates from IKONOS satellite images with spatially extensive and low-cost Landsat ETM+ estimates. The study is unique, as the bias estimator is developed from area-frame samples of high spatial resolution satellite images, instead of aerial photographs or field surveys. A classification model was developed using logistic regression with spline functions to capture nonlinear relationships between crop probabilities and continuous predictors in a generalized additive model framework. Land-cover derived from the International Livestock Research Institute woody biomass maps and the Shuttle Radar Topography Mission (SRTM)-based elevation and slope were used to refine initial estimates. District-level estimates of CA matched a set of independent estimates quite well. The bias estimator provides a first estimate for continued annual CA monitoring using medium resolution satellite imagery, or a methodology for annual bias estimation.

2. Materials and Methods

2.1. Study Area and Data

[8] Ethiopia is situated along the borders of Djibouti, Eritrea, Somalia, and Sudan in east-central Africa (33°00′–47°59′E longitude and 14°53′N–3°24′S latitude). The study area for this project (Figure 1) is the primary crop production zone of Ethiopia and is highly contentious, in terms of national crop production estimates. The terrain of central Ethiopia is complex, as several irregular mountain ranges (highest point = 4385 m) on the Ethiopian plateau are split from northeast to southwest by the Great Rift Valley (lowest point = 603 m). Central Ethiopia has three main seasons, driven primarily by the interaction of terrain with the north-south movement of the Intertropical Convergence Zone: *Belg* (February–May), *Kiremt* (June–October), and the dry *Bega* (November–January) seasons. The region receives 1094 mm of rainfall on average each year, with more occurring in the *Kiremt* season (157 mm/mo) and less in the *Belg* season (63 mm/mo). The dominant field crops (cereals and grains) and pulses are sown at the end of the *Belg* season and harvested at the end of the *Kiremt* season, while secondary crops (e.g., potatoes and yams) are sown at the beginning of the *Belg* season and harvested at the beginning of the *Kiremt* season [*FAO*, 2006a].

[9] High and moderate resolution images were provided by the USGS EROS Data Center in Sioux Falls, SD. Seventeen one meter panchromatic IKONOS images stratified over three 30 m Landsat 7 ETM + scenes were used to determine bias in Landsat CA. The remaining five Landsat scenes were used to estimate CA using the bias estimator. Images were relatively cloud free (<1% cloud cover) and registered in a Lambert Equal Area Azimuthal projection (datum WGS-84). IKONOS images were taken during various stages of crop development in the *Kiremt* season (May, June, July, and October of 2006), while Landsat images were taken at the end of the growing season (October and November of 2005). The timing of Landsat images facilitated classification, as emergent crops and harvested plots were characteristically different from other photosynthetic vegetation, while crops and other photosynthetic vegetation were easily discernable in the high resolution images throughout the growing season. Data constraints limited the acquisition of high resolution imagery for 2005. Given the extent and timing of rainfall, the use of more fertilizer and improved seeds, and lack of major disease outbreaks or pests, 2005 and 2006 represented bumper harvests in Ethiopia [*FAO*, 2006a]. It was therefore assumed that the annual difference in CA for these 2 years was negligible. Colocation error in Landsat and IKONOS images was compensated for by performing analysis on multipoint areas, where the points represent an estimate of areal characteristics.

[10] Slope and elevation were determined from the mosaics of the SRTM 90 m digital elevation model (DEM) for Africa. Post-processing of the SRTM DEM was performed by FAO-SDRN (Environmental and Natural Resources Service). Land-cover information was collected from the International Livestock Research Institute multi-

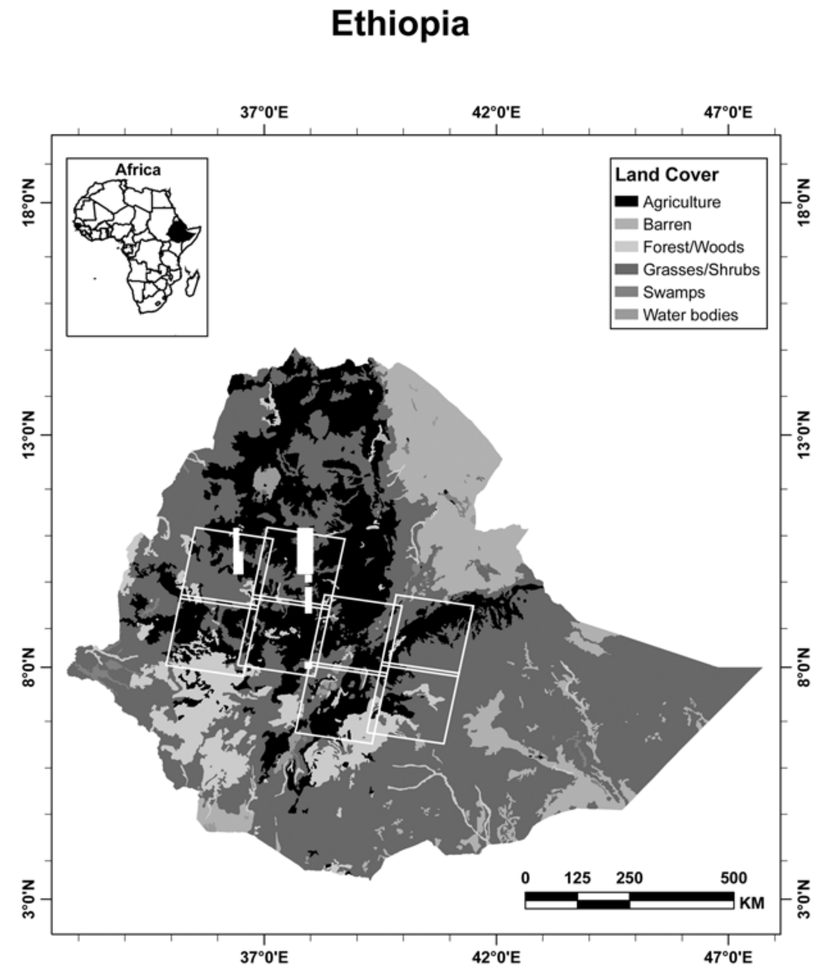

Figure 1. Map of available Landsat scenes and generalized landuse map derived from a Regional Land Management Unit (RELMA) and United Nations Environmental Programme (UNEP) product.

purpose woody biomass database for Ethiopia, a harmonized compilation of land cover maps and corresponding attribute tables. The product was developed from satellite interpretation, national forest inventories, general forest assessments, and biomass studies for the year 2000. The maps contain unique geometric units linked to attribute tables with information on the percentage and type of primary and secondary land cover.

2.2. Area Frame Analysis

[11] Manual interpretation of the digital imagery was performed using the LCMapper tool developed at the USGS EROS Data Center. The manual interpretation used classic heads-up techniques incorporating the color (spectral), shape, texture, shading and pattern information. In the interpretation process, the grid of points was overlaid on the digital imagery, appearing as dots on the image. The LCMapper tool allowed for the selection of dots both individually or in clusters, and the selected dots could then be assigned a crop or no-crop attribute code. The scale of interpretation was dependent on a variety of factors, including the complexity of the landscape, the need for contextual information, and, most importantly, the type of imagery being interpreted. Classification of Landsat imagery was performed using composites that enhanced photosynthetic vegetation (bands 5 = 1.55–1.75 μm, 4 = 0.76–0.90 μm, and 3 = 0.63–0.69 μm). The crop/no-crop points classified included elevation and slope from the SRTM data set and a land-cover class based on the woody biomass data set. IKONOS imagery and corresponding Landsat images were related using a high-frequency sampling regime, while remaining Landsat images used in interpretation of the bias estimator were sampled at a coarser frequency.

[12] High-frequency sampling consisted of setting up a regular grid of points at a 500 m interval across the area covered by the IKONOS imagery. This technique resulted in over 22,000 noncloud samples, which corresponded to high-frequency Landsat classification. Comprehensive sampling consisted of a regular grid of points at a 2 km interval covering the eight Landsat scenes used in this exercise. This resulted in over 80,000 non-SLC-off samples used in deriving the district CA estimates.

2.3. Statistical Analysis

[13] Since the response variable (high resolution land cover) is binary, ordinary linear modeling is not appropriate, so a related alternative approach, logistic regression, was used instead. Logistic regression is a type of generalized

Table 1. Threshold Probabilities for Classifying as Cropped

Land-Cover Class	Probability
Cultivated few	0.69
Cultivated light	0.53
Cultivated moderate	0.46
Grassland	0.32
Shrubland	0.19
Other	0.39

linear model [*McCullagh and Nelder*, 1989] that produces predictions of probabilities for binary response variables. Specifically, a linear model is used to predict the natural log of the odds ratio:

$$\log\left(p \Big/ (1-p)\right) = \beta_0 + \sum_{j=1}^{k} \beta_j x_j + \varepsilon$$

[14] Predictions of probabilities are obtained by taking the exponential of the logit predictions. In this study, p is the probability that a particular location is being cropped.

[15] Logistic regression works equally well with continuous or discrete predictors, but the basic implementation does assume linear relationships between continuous predictors and the log odds ratio. There is reason to expect, however, that elevation and slope are not linearly related to the log odds ratio, so the predictor variables were incorporated into the logistic regression model using flexible smoothing spline models in a generalized additive model framework [*Hastie et al.*, 2001].

[16] Skill in classifying individual pixels and in calculating total number of cropped pixels was estimated using a randomized cross validation approach. The data set was repeatedly divided randomly into two subsets, a training set consisting of 80% of the observations and a test set consisting of 20% of the observations. Models were fit to the training set and then applied to the test set to calculate misclassification error rates and bias and root mean square error of CA estimates.

[17] Currently, estimates of CA in Ethiopia are produced by two governmental agencies, the Central Statistics Authority (CSA) and the Bureau of Agriculture and Rural Development (BoARD). These agencies utilize different techniques for estimating CA. The CSA uses statistical techniques to select a subset of survey locations for deriving their estimates. In addition, the CSA estimates do not include large-scale commercial farms. In contrast, the BoARD has a large network of agents in the field surveying many farms and aggregating that information to derive their cropped area estimates. For the Amhara region, the two agencies have come to a consensus and agreed on a common estimate of cropped area in this region [*FAO*, 2006a]. Typically, the BoARD reflects a higher CA than the CSA. For all the regions provided in the FAO 2006 Crop and Food Supply Assessment Mission, the BoARD estimate of CA is over 25% greater than the estimate provided by CSA at the national level. The BoARD estimates were chosen to compare to model output, as they are used annually for needs assessment by the World Food Programme and include CA for large-scale and newly settled farms, and plots on slopes steeper than predefined limits of viable crop production [*FAO*, 2006a]. The area-weighted average of these estimates resulted in a CA percent for each district, which was then multiplied by the area of the district to arrive at the CA for the district.

3. Results

[18] Five land-cover classes comprised nearly 84% of the high-frequency points, with the other 16% being dispersed among 15 land-cover classes. Because of this, the five dominant classes (cultivated few stocks, cultivated light stocks, cultivated moderate stocks, dense shrubland, and grassland few stocks) were placed into individual categories, while the remaining 15 classes found in the land-cover map were combined into an ‘‘other’’ class. The study area is comprised primarily of sparse cropland and grasses (cultivated few stocks = 32.3% and grassland few stocks = 32.0%). Cultivated light stocks, cultivated moderate stocks, dense shrubland, comprise 8.9%, 4.7%, and 5.7% of the remaining land area respectively. The overall accuracy of predicted crop and not crop for the moderate resolution classification with ‘‘truth’’ (high resolution classification) was 71.2%. Omission errors were lower for agriculture (15.4%) than for nonagriculture (37.1%), however commission errors were higher for agriculture (41.6%) than nonagriculture (13.1%). Overall accuracy within each class was highest for the ‘‘other’’ class (81.7%), followed by dense shrubland (76.7%), cultivated few stocks (74.9%), grassland few stocks (65.8%), cultivated light stocks (62.4%), and cultivated moderate stocks (55.5%).

[19] Due to the variations in misclassification rates for different land-cover classes, separate classification models were fit individually for each class using moderate resolution classification, elevation and slope as predictors. The threshold probabilities for classifying a pixel as cropped were determined for each land-cover class to approximately equalize omission and commission errors. These are shown in Table 1. The classification results (Table 2) show the impact of the variable classification thresholds on equalizing the two types of errors. The accuracy of the model improves to 76.9% correct, in comparison to the 71.2% correct using only the moderate resolution classification. For individual land-cover class, the accuracy ranges from a low of 63.0% for cultivated light to a high of 89.7% for shrubland. Overall, the set of six models explained 33.6% of the deviance (analogous to R Squared for logistic regression models).

[20] Under cross validation the misclassification error rate remains nearly the same, dropping slightly to 76.4%. The

Table 2. Classification Results

Land-Cover Class	Correct Crop	Correct Noncrop	Commission Error	Omission Error
Cultivated few	0.553	0.182	0.133	0.131
Cultivated light	0.335	0.276	0.192	0.178
Cultivated moderate	0.325	0.348	0.165	0.162
Grassland	0.077	0.703	0.111	0.108
Shrubland	0.023	0.873	0.054	0.050
Other	0.078	0.803	0.059	0.059

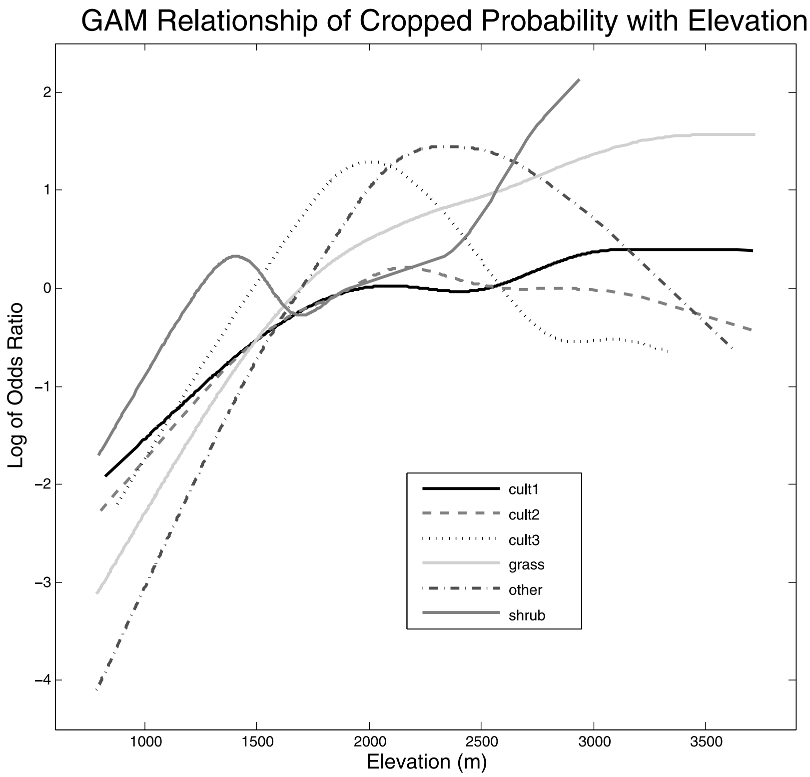

Figure 2. Relationships between elevation and log of odds ratio.

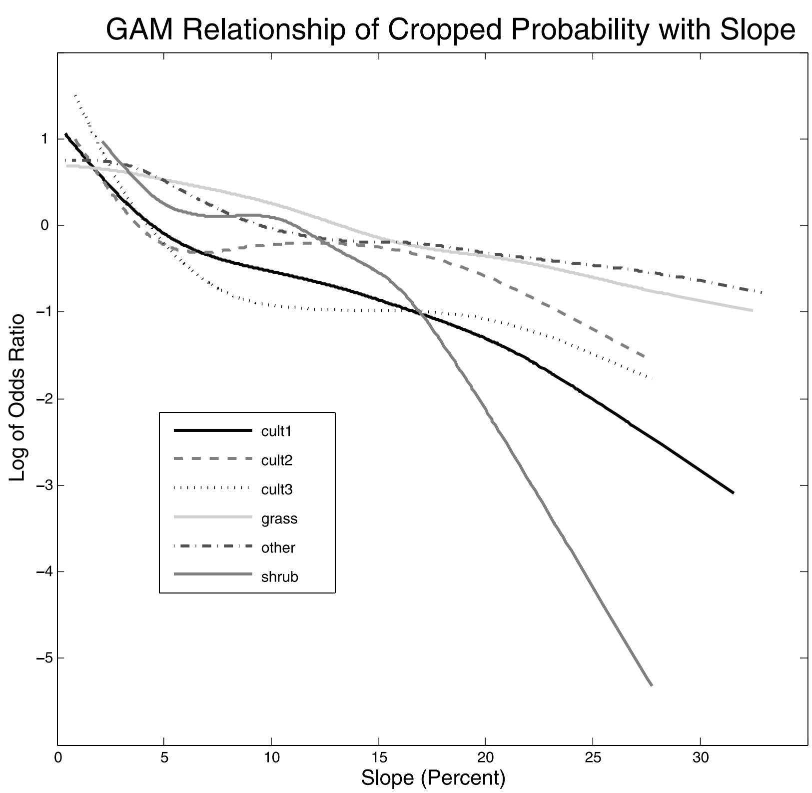

Figure 3. Relationships between slope and log of odds ratio.

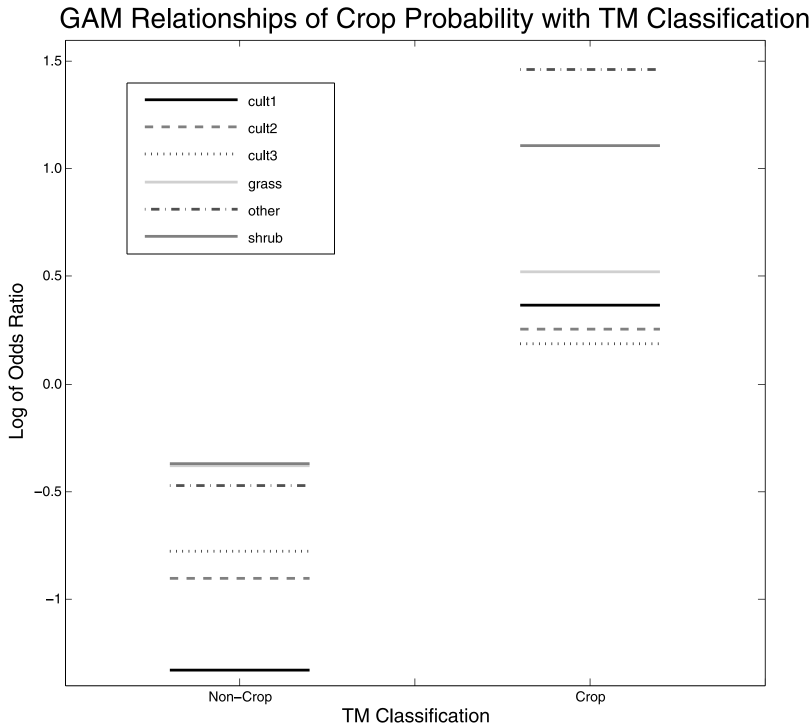

Figure 4. Relationships between moderate resolution classification and log of odds ratio.

cross validated predictions of total CA have an average bias of 1.2% and a root mean square error of 3.9%.

[21] The relationships with the three predictors also varied by land-cover class, although the general trends were similar. The relationships with elevation are shown in Figure 2. In all land-cover classes cropped, probability increases with higher elevation up to approximately 2000 m, after which it tends to level off. The relationships with slope (Figure 3) show monotonically decreasing log odds ratio with increasing slope. In most cases, there is a relatively rapid decrease moving away from flat areas, followed by a less rapid decrease at higher slopes. The relationships with moderate resolution classification are positive in all land-cover classes (Figure 4) with moderate resolution classification of CA, increasing the odds ratio by a factor ranging between 1.6 and 2.1.

[22] Comparisons with district-level ground estimates are presented in Table 3. Both sets of estimates correlate generally well with the remote sensing estimates. The total for the BoARD estimates matches much better with the remote sensing estimates than do the CSA estimates. On the basis of the cross validated RMSE of 3.9%, the range for the remote sensing estimate is 3194–3460 which easily includes the BoARD estimate but not the CSA estimate.

4. Discussion

[23] The intent of this study was to confirm the CA numbers from one of the agencies. For our study area the BoARD estimates were 40% greater than the CSA estimates, creating large uncertainty in the production estimates for the region. The confirmation of the BoARD estimate has wide-reaching implications for Ethiopian government entities, such as the Ministry of Agriculture, The Disaster and Preparedness Agency, the Ethiopian Trading Enterprise and international agencies like the World Food Programme and Famine Early Warning System Network which monitor food insecurity in the country.

[24] The difficulty of obtaining concurrent high and medium resolution imagery was a limitation and has been resolved since the completion of this preliminary study. The seasonal differences aided in interpretation of the medium resolution imagery, while the annual differences were assumed to be negligible. The assumption is valid, as the 2005 and 2006 growing seasons were similar and well above average in terms of CA and production. Other periods have seen dramatic annual differences. For example, large decreases in CA in 2001, followed years of increased crop supply and price cuts. The robustness of this method, particularly during below average years remains an integral step in model development.

Table 3. Comparison of Cropped Area Estimates (Thousands of Hectares)

District	BoARD Estimates	CSA Estimates	RS Estimates
Yem	13	14	10
Sidama	147	72	262
Gurage	144	81	241
N. Shewa	534	350	409
E. Shewa	608	470	566
W. Harerge	199	200	173
E. Wellega	414	309	326
Arsi	733	551	653
W. Shewa	639	426	683
Total	**3465**	**2490**	**3327**
R-square with RS	0.92	0.86	
Slope with RS	1.06	0.76	

[25] Manual interpretation of the high and medium imagery was a lengthy process (~3 man months), however when considering the final goal of this research, which is to implement the method in regional offices throughout Africa, the cost-effectiveness and efficiency of using a hybrid remote sensing model over traditional sampling regimes is clear. The bias estimator developed here can be used in future growing seasons with the latest free medium and high resolution imagery for initial estimates, while a more in depth analysis involving reevaluation of the bias estimator to accommodate temporal uncertainties will follow. Segmentation methods are currently being evaluated to automate the classification process and thus further reduce the time and cost of CA estimation. Segmentation has a obvious advantage over spectral techniques, as it relies on the structure and not the spectral separability of a given land-cover class.

[26] Interpretation of the different variables used in the logistic regression relates some of the important physical factors to the probability of a location being cropped. From the elevation variable we see that low elevations have a reduced probability of being cropped, likely due to reduced rainfall, increased temperatures, and increased disease risk. As elevation increases, so does the probability of crop, until at a little more than 2000 m there is a leveling off for almost all land-cover classes. This represents the optimal blend of precipitation and temperature, above which there is no further improvement in probability of crop, and in some land-cover classes we see a reduction above this elevation. The slope variable shows the flat locations are the most likely to be cropped; as the slope increases the likelihood decreases. There is a steep drop in probability of crop from 0–5% slope, after which the slope contribution is steady until steeper than 20% when the probability again starts to drop dramatically. Classification of the moderate resolution data shows a meaningful increase in probability of crop for all classes, revealing that the characteristics of CA are somewhat interpretable even without being able to distinguish specific features such as crop rows, field boundaries or other items that distinguish crops in the high resolution imagery.

[27] The "other" class is a conglomeration of land-cover types. While it composed only 15% of the area covered by the high resolution imagery, it made up nearly 40% of the area covered by the Landsat data. So, while the percentage error was small for the "other" class, even a slight improvement in the error percentage could result in a large overall improvement because it is so much of the landscape. As the component classes of the "other" invariably shift outside the high resolution area, the model developed for the high resolution area could be inadequate.

[28] Errors seen in the cross validated accuracy value of 76.4% are due primarily to misclassification and coregistration between satellite imagery, the DEM, and land-cover maps. The relatively high commission and low omission error for agriculture indicates that overestimation of agriculture is due to a large extent by classification of noncrop as crop. Prior studies involving automated classification techniques of medium resolution imagery have noted the overestimation of CA as well, as spectral classifiers are limited in determining unique signatures for mixed pixels. It appears that the use of a manual technique with high resolution imagery only marginally reduces high commission errors, when land-cover is not taken into account. This reflects the idea that crop may look different on satellite imagery or have different characteristics for different land-cover. Although coregistration and misclassification errors are reduced when aggregating points to district level estimates of CA, the real advantage of this technique in improving overall accuracy lies in the use of class-specific thresholds. Treating the different land-cover classes independently differentiates this study from previous research.

[29] The correlation between CA estimates of the two published figures with the estimates in this study may be a bit misleading. The difference in district size is partially built into the R-square statistic presented in Table 3. Large districts are likely to have large CA, while small districts are likely to have small CA. However, errors in percent of area cropped have different meaning for districts of different sizes, with large percentage errors being less important for small districts in determining the overall CA. When comparing the percentage of area cropped the R-square is still a respectable 0.48, meaning that nearly half of the variability in cropped percentage is captured with this method. Since one of the goals of the study is to get an estimate of CA, it is important to look at the slope between the two reported figures and the method presented here. The slope for the BoARD is quite close to 1.0, indicating that overall the bias between the estimates derived in this study and those of the BoARD are insignificant. The slope coefficient for the CSA statistics is 0.76, indicating the CSA estimates are roughly three-fourths of the estimates found in this study.

[30] Large differences between district estimates made in this study and those of the BoARD can be attributed to the distribution of high resolution images used to derive the bias estimator. For example, Gurage and Sidama, which both showed significant differences between BoARD estimates and estimates made in the study, happen to fall in areas which were quite far from the available high-resolution imagery used to build the models in this work. The model, therefore, may not be as representative in these locations. Gurage and Sidama are also large-scale coffee producing regions, suggesting that our models overestimate CA in this land-cover type. Future efforts should be aimed at ensuring a representative sample of high-resolution imagery is acquired in order to build a model that adequately models all possible landscapes found in the study area.

5. Conclusions and Implications

[31] This study defines a credible and objective method for determining CA using remotely sensed interpretations of high resolution (~1 m) and moderate resolution (~30 m) satellite imagery, physical characteristics and land-cover maps. High resolution imagery is used to remove bias in cropped estimates derived from the interpretation of moderate resolution imagery, given land-cover and DEM information. The results of this study support the CA in Ethiopia as estimated by the BoARD.

[32] Using land-cover specific thresholds to determine the appropriate probability to define a point as crop, it is possible to balance commission and omission errors when applied over large areas. This results in providing an unbiased crop percentage for each land-cover type over

the area covered by the high-resolution imagery. As long as the high-resolution imagery covers a representative sample of the larger region extending this threshold to the entire study region will lead to an improved, unbiased estimate of CA. It is reasonable to assume that similar relationships exist between slopes, elevation, and CA in regions outside the primary crop producing zone, as the driving factors are consistent throughout the country, however with improved satellite coverage, the model should be evaluated in more arid regions.

[33] This study presents a technique for estimation of cropped area based on satellite imagery in a statistically objective and timely manner. The results of this study for Ethiopia in 2006 confirm one set of existing government estimates. The impacts of this study show the promise for timely and objective cropped area estimates in the future, potentially reducing the debate over which estimates the government and donor agencies use in the design of food security programs and emergency response to a food crisis. The concept of accepting one model for CA, as well as the low cost and efficiency of it, would give local, national, and international stakeholders more time to respond to food insecurity and poverty reduction.

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