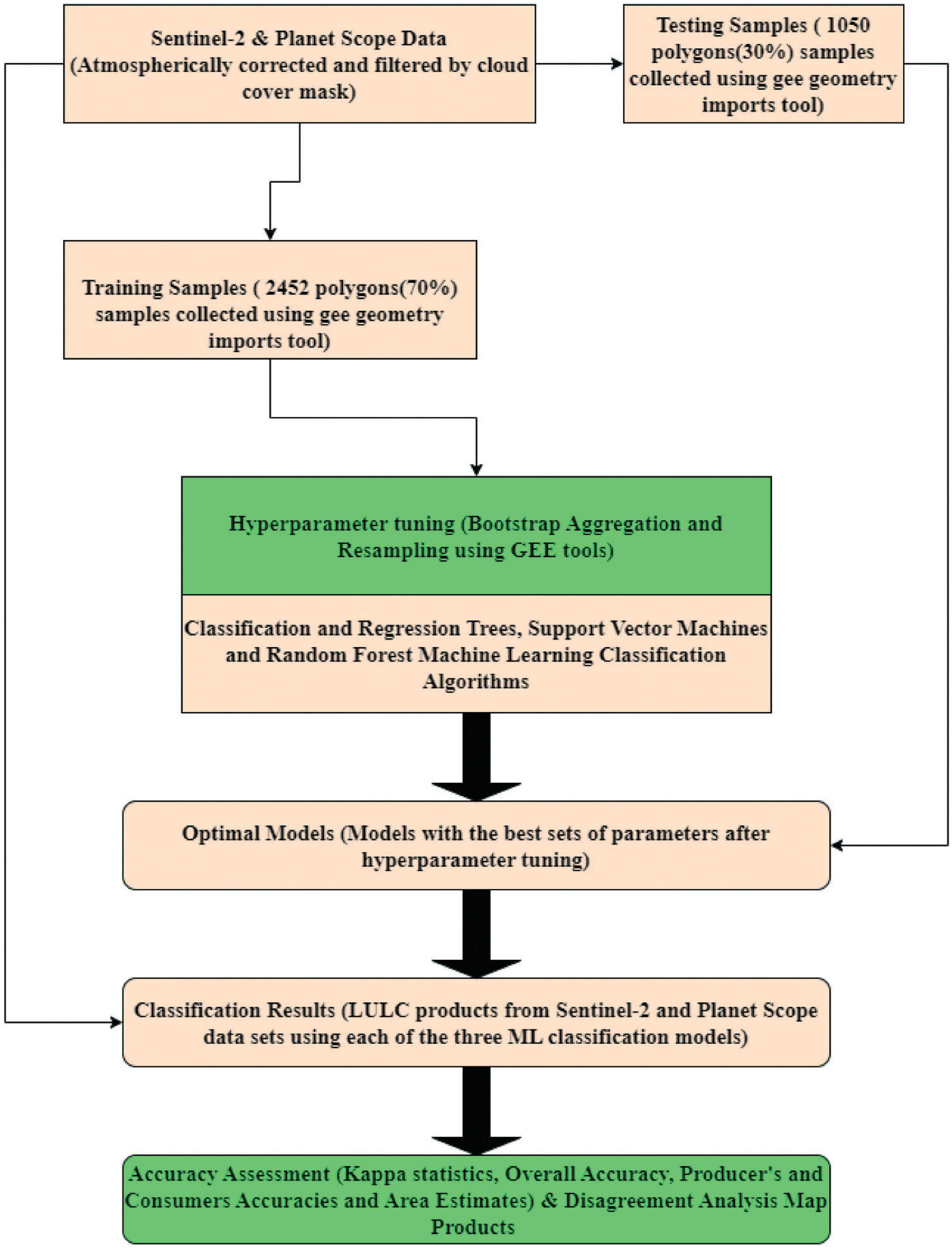

Figure 4. Flowchart of methodology.

cropland is primarily confined to the Kilombero Valley, a region predominantly assumed to be experiencing suitable weather conditions for agricultural practices. Equally likely, the flat topography and the fact that water from regular floods can be extracted and used for irrigation is a befitting agricultural advantage for Kilombero Valley (Thonfeld et al. 2020).

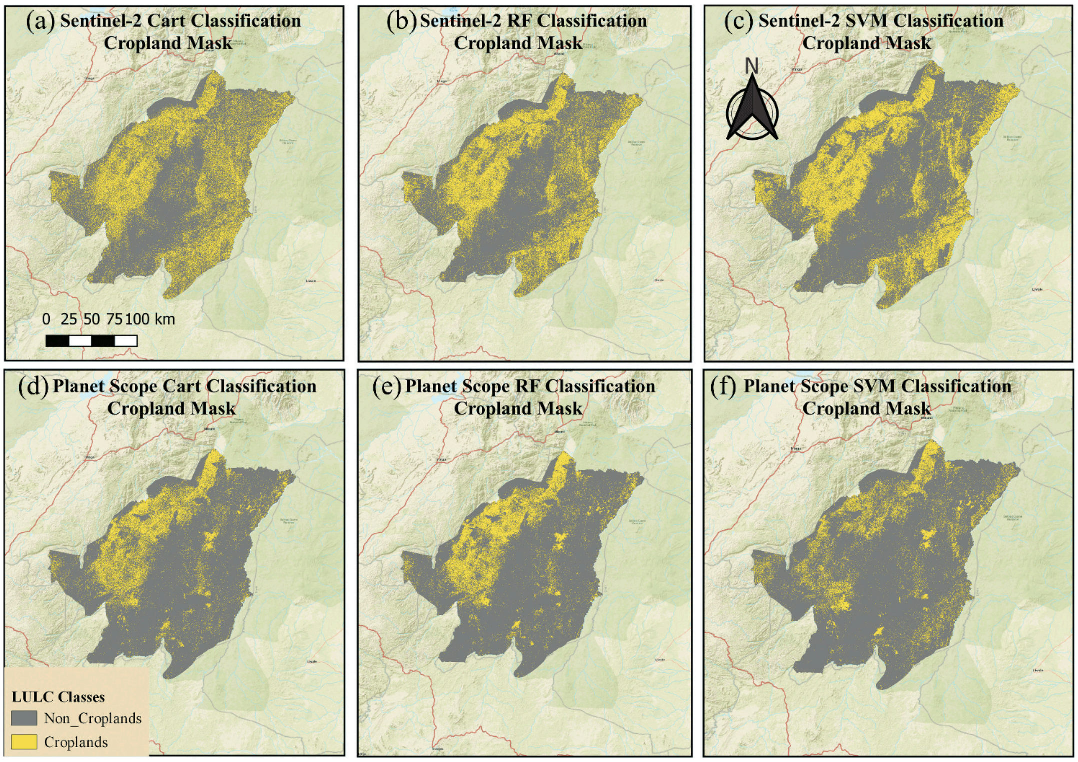

Figure 5. Maps of LULC binary analysis results created from Sentinel-2 and PlanetScopedata. a) LULC binary analysis results obtained from Sentinel-2 data using the Cart algorithm. b) LULC binary analysis results obtained from Sentinel-2 data using the RFalgorithm. c) LULC binary analysis results obtained from Sentinel-2 data using the SVMalgorithm. d) LULC binary analysis results obtained from PlanetScope data using the Cart algorithm. e) LULC binary analysis results obtained from PlanetScope data using the RFalgorithm. f) LULC binary analysis results obtained from PlanetScope data using the SVMalgorithm.

Figure 6c, Figures 6f, and 6i illustrate the level of cropland disagreements between Sentinel-2 PlanetScope data using Cart, RF, and SVM classification algorithms, respectively. While there is evidence of dense croplands concentrated almost entirely in the Kilombero Valley among all the ML models, it is also clear that there exists disagreement between LULC maps obtained from Sentinel-2 and PlanetScope data. In the Eastern part of the study area, LULC cropland masks generated from Sentinel-2 data disagree with those generated from PlanetScope data as depicted by the greenish-blue colour. Also in Kilombero Valley, there exists slight disagreement in the cropland masks shown by the orange colour. Figure 6f reveals lower levels of disagreement than the other classification algorithms. Consequently, this implies that the RF classifier has shown better results in categorizing croplands in both Sentinel-2 and PlanetScope datasets compared with the other classification algorithms. Generally, the RF classification algorithm outperforms other machine learning models in most land cover classification studies. Still, different machine learning algorithms sometimes work better with varying sets of data and must be tested case by case (Ramezan et al. 2021; Rana and Venkata Suryanarayana 2020; [csl:31]; Thanh Noi and Kappas 2017).

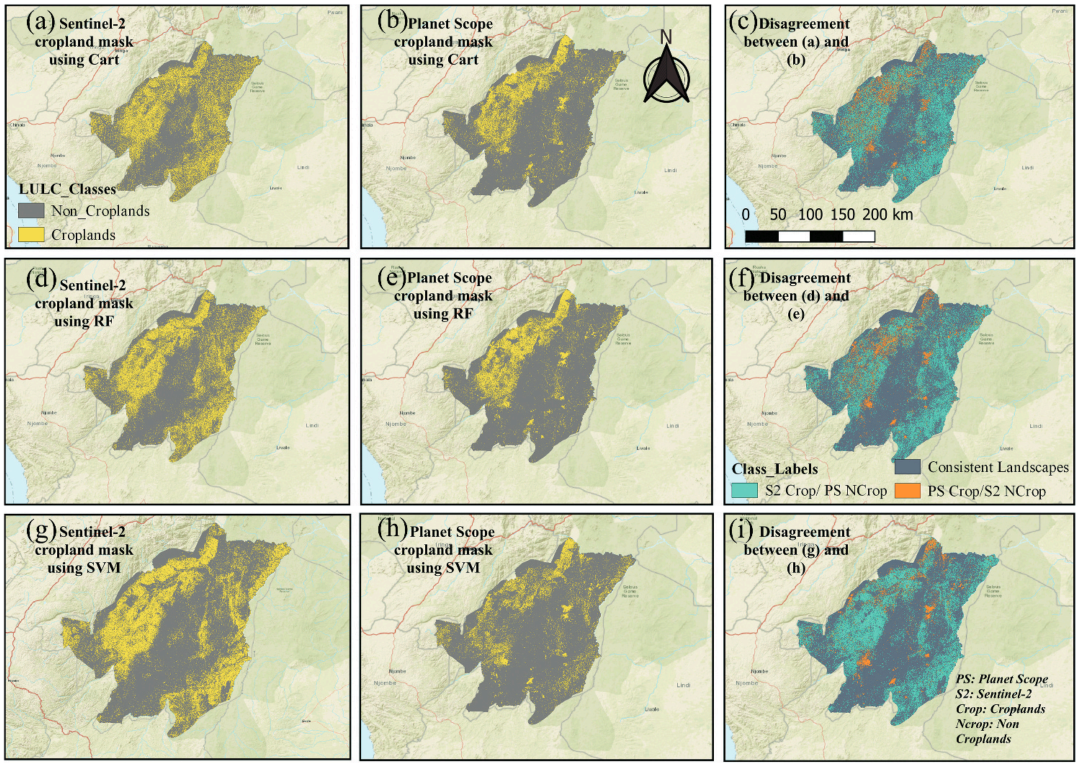

Figure 6. Maps of cropland disagreement generated from PlanetScope data and Sentinel 2 classification maps. a) Sentinel-2 CART classification cropland mask. b) PlanetScope Cart classification cropland mask. c) Disagreement between PlanetScope and Sentinel-2 cropland masks based on Cart classification. d) Sentinel-2 RF classification cropland mask. e) PlanetScope RF classification cropland mask. f) Disagreement between PlanetScope and Sentinel-2 cropland masks based on RF classification. g) Sentinel-2 SVM classification crop land mask. h) PlanetScope SVM classification cropland mask. i) Disagreement between PlanetScope and Sentinel-2 cropland masks based on SVM classification.

Table 5 illustrates that an average of 7% of the study area originally classified as cropland from PlanetScope data using the three classification algorithms is controversially non-cropland according to the classification of Sentinel-2 data. On the other hand, an average of 22% of the total pixels in the study area originally classified as cropland from Sentinel-2 data is controversially non-cropland according to PlanetScope data classification. Generally, 71% of the pixels are consistently classified as either cropland or non-croplands by all the classification approaches on average.

Table 5 reveals that according to RF and SVM classification, 27% of the pixels in the study area disagree between cropland and non-cropland classes based on the cropland masks making them preferable to the CART classifier in such dynamic landscapes as those in the sub-Saharan region. PlanetScope high-resolution data generally produced fewer inaccurate classifications compared to coarser Sentinel-2 further reveals that the cropland class is mostly confused with the woodlands class compared to Sentinel-2 but not as much with other land cover classes.

This study found that Sentinel-2-based classification is very sensitive to croplands followed by other vegetation cover with very low sensitivity to the built-up area and bare soil classes as in Figure 7. On the other hand, PlanetScope-based classification recognized more built-up and bare soil classes with more vigour than vegetation cover

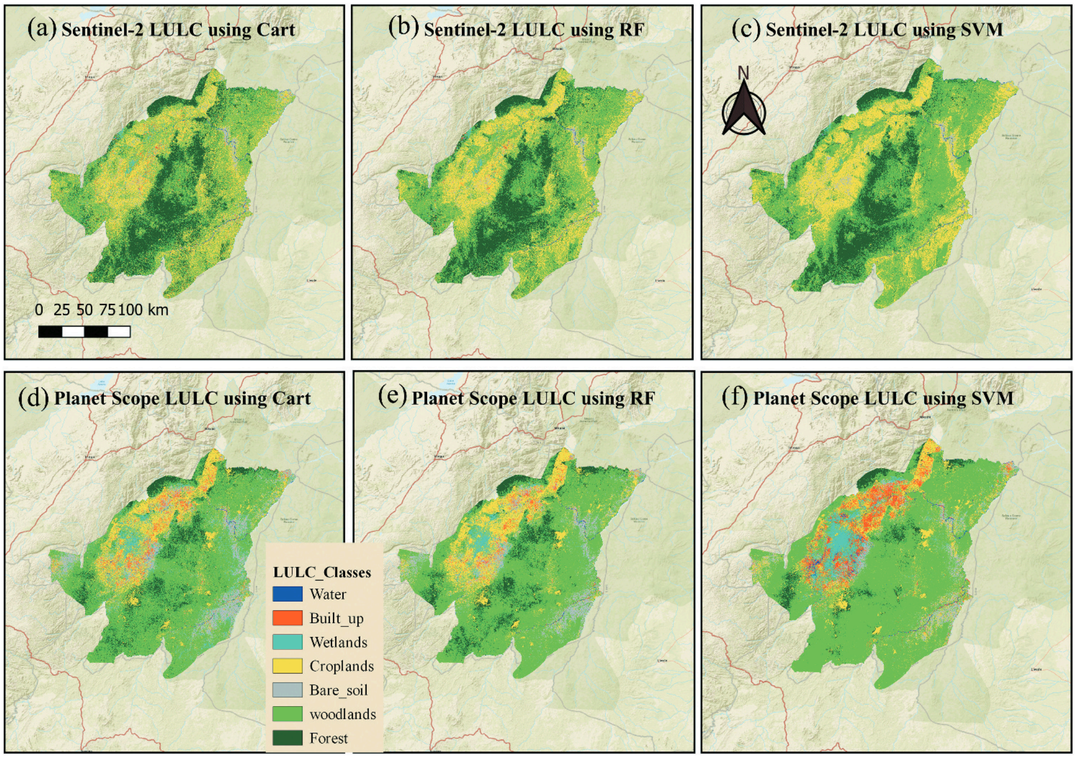

Figure 7. Maps of LULC created from Sentinel-2 and PlanetScope data. a) LULC classes obtained from Sentinel-2 data using the Cart algorithm. b) LULC classes obtained from Sentinel-2 data using the RF algorithm. c) LULC classes obtained from Sentinel-2 data using the SVM algorithm. d) LULC classes obtained from PlanetScope data using the Cart algorithm. e) LULC classes obtained from PlanetScope data using the RF algorithm. f) LULC classes obtained from PlanetScope data using the SVM algorithm.

Table 5. Disagreement assessment results.

	PixelSum and Percentage					
Class labels	Cart	%	RF	%	SVM	%
Planet(Cropland)/Sentinel(Non-cropland)	3106752	8	2667101	7	1998978	5
Sentinel(Cropland)/Planet(Non-cropland)	9034096	23	8022079	20	8921153	22
Consistent Landscapes (Agreement)	27924559	70	29376227	73	29145276	73

as in Figure 7. The sentinel-based classification over-detects crop cover compared to classifications based on PlanetScope data. This implies that PlanetScope data is best suited to distinguishing the discrepancies between vegetation cover where most disagreements have been realized.

Table 6 represents a summary obtained from our accuracy assessment criteria and area estimates according to each classification algorithm on the respective datasets. Table 6 shows that RF achieved the highest overall classification accuracy of 93% on PlanetScope data and 91% with Sentinel-2 data which outperforms all the other classification methods in this study. Consequently, we obtained a kappa statistic of 0.9 on both Sentinel-2 and PlanetScope datasets using the RF classifier. Generally, our results show that RF has outperformed the other two classification paradigms.

Table 6. Accuracy assessment results.

LC Class	Area estimates according to different classifiers in Square Metres					
Data source	Planet Scope			Sentinel-2		
Classifier	CART	SVM	RF	CART	SVM	RF
Water	21	75	26	28	21	34
Built_up	719	1875	385	541	29	214
Wetlands	1748	1564	819	43	114	451
Croplands	5651	5193	5786	14830	10752	11677
Bare_soil	4856	2479	4131	199	425	476
Woodlands	18417	22893	20973	15529	17486	14679
Forest	3992	1324	3284	4233	6577	7872
Accuracy Assessment						
Overall Accuracy %	89	83	93	86	76	91
Kappa Statistic	0.9	0.8	0.9	0.7	0.7	0.9

Table 7. Average area estimate results from PlanetScope and Sentinel-2 classifications.

Average and percentage land cover area of PlanetScope and Sentinel-2 classifications.

Land Cover Class	Planet Scope		Sentinel-2	
	Average Area M^2	Percentage %	Average Area M^2	Percentage %
Water	40	0.1	28	0.1
Built_up	993	2.8	261	0.7
Wetlands	1377	3.9	203	0.6
Croplands	5544	15.7	12420	35.1
Bare_soil	3822	10.8	367	1.0
Woodlands	20761	58.6	15898	44.9
Forest	2867	8.1	6227	17.6
Total Area	35404	100	35403	100

Table 7 further illustrates the average and percentage land cover area per class according to the classifications based on Sentinel-2 and PlanetScope datasets. In both datasets, the water class covers the smallest area contributing to less than 1% of the study area. On the other hand, the most prominent land cover class (woodlands: other vegetation different from croplands and forests) disagrees significantly in area estimates with PlanetScope woodlands contributing to almost 59% while sentinel-2 average area represents almost 45%.

Based on the results from our classification accuracy assessments in Tables 5, 6 and 7 , Table 8 highlights the User's and Producer's accuracies based on the confusion matrix used for accuracy assessment for our results. Table 8 also presents a summary of the comparison paradigm meant to identify any significant differences in the accuracies obtained from respective data sets based on a 95% confidence interval. With an overall Z-statistic of 0.2015 and an associated $P - value$ of 0.84, it is concluded that there is no significant difference between the accuracies obtained from Planet Scope data and those from Sentinel-2 implying that both data sets were essential in LULC categorization. Since the $P - value = 0.84 > 0.05$ at 95% confidence level, we conclude that there is not enough evidence to reject the null hypothesis and hence it is upheld.

Machine learning unsurprisingly appears to work much better with high-resolution data as compared to coarse-resolution data sets. Individual plots are more likely to be homogeneous in PlanetScope data making RF more precisely trainable. We recognize that PlanetScope's high-resolution data is much less likely to have pixel confusion during

Table 8. Producer's accuracies, User's accuracies and Z-Statistics.

	WT	BU	WL	CL	BS	WL	TC	R.Total	UA	Z-Statistic (95% C.I)	P-value
Planet Scope											
WT	38	1	0	0	0	0	0	39	1.00		
BU	0	59	1	7	1	3	0	71	0.45		
WL	0	0	110	22	0	18	0	150	0.89		
CL	0	0	5	730	7	129	3	874	0.96		
BS	0	0	0	12	519	10	0	541	0.63		
WL	0	0	4	87	0	1227	13	1331	0.94		
TC	0	0	0	0	0	12	484	496	0.97		
C.Total	38	60	120	858	527	1399	500	3502			
PA	1.00	0.17	0.80	0.95	0.54	0.96	0.97				
OA	88										
Kappa	0.9										
Sentinel-2										0.2015	0.84
WT	41	1	0	0	0	0	0	42	0.99		
BU	0	56	0	8	0	0	0	64	0.84		
WL	0	0	107	20	0	19	1	147	0.88		
CL	0	2	4	725	8	141	2	882	0.75		
BS	0	0	0	10	552	9	0	571	0.96		
WL	0	0	0	71	0	1178	13	1262	0.81		
TC	0	0	0	0	0	15	519	534	0.96		
C.Total	41	59	111	834	560	1362	535	3502			
PA	0.96	0.57	0.63	0.70	0.94	0.89	0.95				
OA	84										
Kappa	0.8										

classification than Sentinel-2 data, particularly where vegetation cover is low. For example, in the eastern parts of the study area, Sentinel-2 confuses non-cropland landscapes for potential farmlands when a classification attempt is made. PlanetScope on the other hand clearly distinguishes the landscapes to bring forth a more reliable cropland mask because of its high spatial resolution making it possible to obtain accurate data for training the machine learning algorithms. That notwithstanding, PlanetScope can not be used to derive cropland masks independently with absolute certainty and hence the need for collecting more ground truth reference data for training ML models. Additionally, farms close to wetlands are mostly confused with wetlands incorrectly when Sentinel-2 data is classified. With this understanding, we observed that PlanetScope outperforms Sentinel-2 in all machine learning algorithms given its classification overall accuracy and Kappa Statistics, and hence preferably produces a more reliable cropland mask.

5. Conclusions

This study reveals compelling evidence of cropland disagreements based on a direct disagreement assessment criterion using LULC cropland masks obtained from Sentinel-2 and PlanetScope classification using CART, RF, and SVM classification algorithms at a sub-national scale. Using atmospherically corrected cloud-free median composites at 10 m and 4 m spatial resolutions for Sentinel-2 and Planet Scope respectively, we performed LULC classification and obtained respective cropland masks corresponding to the various classification paradigms. For machine learning algorithm training, we used a total of 2452 samples to evaluate our models, and assessed their performance accuracies based on 1050 samples.

The combination of high-resolution data with machine-learning approaches is likely to improve cropland cover identification in low ground-truth areas and these results suggest that for semi-arid tropical regions, RF is a preferred approach using PlanetScope data because of its ability to train on very representative and distinct data (more and smaller pixels for sampling). However, SVM performed better on the coarser Sentinel-2 data based on the continuity and uniformity of the cropland mask and is recommended if higher-resolution data are not available for semi-arid regions. Misclassification is likely to be higher for woodland areas with coarser data though.

While high-resolution datasets help in accuracy assessment, our results would improve significantly with ground validation data points. Ground Truth data collected through citizen science and well-guided validation criteria would provide a more reliable way to develop a sustainable, accurate cropland mask periodically over time using a supervised machine learning classification preferably RF and SVM.

The use of Landsat time-series data has proved relevant in mapping cropland extent and extensive crop-type mapping in developed countries like the U.S.A. and in Europe (Johnson 2019; Xie and Lark 2021). However, due to multi-cropping systems and varied landscapes in the sub-Saharan region, Landsat datasets are insufficient for the aforementioned mapping procedures as machine learning classification models often confuse land cover classes. This study has highlighted the hotspots for such confused landscapes and hence more accurate LULC classification results are anticipated through land cover resampling methods.

The two mechanisms recommended in this study i.e. incentivized crowd-sourcing rural agricultural imagery and unsupervised machine learning is observationally equivalent to the available global land cover data, albeit with superior abilities to distinguish and monitor agricultural landscapes over time for accurate change analysis. Collecting fine-grained sub-national data to distinguish between land use types could help to untangle these mechanisms empirically. Additionally, these mechanisms will serve to provide accurate crop cover data to help reduce disagreement and increase agreement between the two classification results based on different satellite imagery. Further, developing a correction method for Sentinel-2 and PlanetScope misclassifications would make for a more rapid and robust crop cover product because PlanetScope data are collected more frequently while Sentinel-2 data cover a larger area and at a lower cost to the map producer.

Accurate cropland masks are needed to predict food insecurity. Sarr (Sarr et al. 2021) illustrates that acceptance of climate change is a key driver of SRI adoption, so cropland mapping initiatives together crop, modelling is key to building more accurate yield projections that will aid in public acceptance and also guide crop breeders in producing the next generation of rice varieties for the implementation of SRI in Tanzania. This study serves to address the gap in the accuracy of cropland mapping. The next steps include repeated, reliable, and consistent ground data collection for validation as crops and cropland under cultivation change from year to year. Ultimately, we would seek to produce consistent annual land cover classification based on more robust methods such as deep learning algorithm products that could be used by the crop modelling community.

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