Using Sentinel-1, Sentinel-2, and Planet Satellite Data to Map Field-Level Tillage Practices in Smallholder Systems

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Abstract

Zero tillage has become more popular among smallholder farmers and understanding patterns of adoption is crucial for evaluating the financial, agricultural and environmental impact of tillage practices on agroecosystems. However, detecting tillage practices is still challenging in smallholder fields (<2 ha) because historically-available satellite data are too coarse in spatial resolution to map individual smallholder fields. In this study, we used newer, higher-resolution satellite data from Sentinel-1, Sentinel-2, and Planet to map tillage practices in northeast India. We specifically tested the classification performance of single sensor and multiple sensor random forest models, and the impact of spatial, temporal, or spectral resolution on classification accuracy. We found when considering a single sensor, Planet imagery (3 m) had the highest classification accuracy (86.55%) and radar Sentinel-1 data (10 m) did little to improve classification accuracy (62.28%). When considering sensor combinations, combining three sensors achieved the highest classification accuracy (87.71%), though this was only marginally better than the Planet only model. We also found that high levels of accuracy could be achieved by using imagery only available during the sowing period. Considering the impact of improved spatial, temporal, and spectral resolution, we found that improved spatial resolution from Planet contributed the most to improved classification accuracy. Overall, it is possible to use readily-available, high spatial resolution satellite data to map tillage practices of smallholder farms, even in heterogeneous systems with small field sizes.

Keywords: tillage; smallholder systems; Bihar; optical and SAR sensors; random forest

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1. Introduction

Conventional tillage (CT) is used to control weeds, incorporate crop residue, and prepare lands for planting, but minimizing soil disturbance, reducing soil erosion, and maintaining soil cover are critical to improving soil health. Over the last few decades, many studies have shown that zero tillage (ZT) has agronomic and economic benefits compared to CT (Keil et al. 2020), (Mondal et al. 2020; Nyborg and Malhi 1989). The amount of land area under ZT has increased steadily since the 1990s (Derpsch et al. 2010), yet quantifying the exact area under ZT has been challenging given that typical methods used to collect such information, such as censuses, are not implemented in all regions of the world due to financial, accessibility, and labor constraints (Kubitza et al. 2020). This is particularly true in smallholder systems, where small-scale studies have suggested that ZT adoption rates have increased steadily in recent years (Kassam, Friedrich, and Derpsch 2019). Understanding ZT adoption in smallholder systems is critically important given that is has been shown to be an important way to sustainably intensify cereal grains in these systems. Remote sensing can offer an alternative and low-cost way to quantify ZT adoption at large spatial and temporal scales.

Numerous detection techniques have been developed to map tillage practices at broad spatial scales (Obade and Gaya 2020; Zheng et al. 2014), yet these approaches may not be suitable for detecting tillage practices in smallholder systems (Azzari et al. 2019; Beeson, Daughtry, and Wallander 2020). This is largely because the size of smallholder fields (< 2 ha) is typically smaller than the spatial resolution of historically-available satellite imagery, such as Landsat (30 m) and MODIS (250 m) (Azzari et al. 2019; Jain et al. 2013), that have typically been used in previous tillage mapping studies. Over the last five years, new low-cost and higher-spatial resolution satellites, such as Sentinel-1 (10 m), Sentinel-2 (10 m) and Planet (3 m), have become available, and studies have shown that these sensors are better able to capture field-level variation of smallholder farms (Jain et al. 2016, 2019; Jin et al. 2019). It is possible that these higher resolution sensors may be able to effectively map tillage practices in smallholder systems, yet to date, no studies currently exist that have used these higher resolution satellite datasets to map tillage practices in smallholder systems.

Previous studies that have used satellite data to map tillage practices have found that using multiple sensors in classification algorithms can improve accuracy. For example, Beeson et al. (2016) found that combining multi-temporal Landsat 5, Landsat 7 and Landsat 8 resulted in increased accuracies compared to using individual sensors. In addition, Azzari et al. (2019) found that combining optical Landsat satellite data and radar Sentinel-1 data led to higher classification accuracies of tillage practices across the United States Midwest, although the contribution of Sentinel-1 data was small. In smallholder systems, it is possible that combining Planet, Sentinel-1, and Sentinel-2 satellite data may improve classification accuracies. Sentinel-1 has the advantage of being insensitive to water vapor and cloud cover, providing data more regularly through time than optical sensors. This is important in smallholder systems given that the majority of

smallholder systems are found throughout the tropics with periods of high rainfall and cloud cover (Jin et al. 2019). Sentinel-2 imagery has multiple spectral bands that cover the visible, near-infrared (VNIR), shortwave-infrared (SWIR), and red-edge wavelengths; red-edge spectral bands are particularly critical for mapping vegetation characteristics (Delegido et al. 2011; Sun et al. 2020). Planetscope imagery has higher spatial resolution, which may reduce the effect of mixed pixels at field edges (Li et al. 2019).

Though previous studies have shown that classification accuracy of mapping agricultural characteristics, including crop type and yield, can be improved by using images throughout the growing season (Jain et al. 2016; Sun et al. 2019; Van Niel and McVicar 2004; Wei et al. 2019), it is possible that only using images during the early part of the growing season may result in high classification accuracies for mapping tillage practices. This is because most spectral and phenological differences are likely to occur at the start of the growing season as fields are prepared and seedlings germinate. Producing accurate maps of tillage practices using only early season imagery could allow for within season mapping of ZT areas; such information could be important for policy makers and decision-makers who could use such maps in real time to target low adoption areas with increased extension services and government services (Marenya et al. 2017).

This study examines the ability of PlanetScope, Sentinel-1, and Sentinel-2 imagery to map field-level ZT and CT of smallholder farms. We focus our study in the state of Bihar in eastern India, which is a region where zero tillage adoption has increased over the last decade (Keil 2017) and where field sizes are very small (< 0.3 ha on average) (Jain et al. 2019). We aim to answer the following questions in this study:

1. How effectively can single sensor and multiple sensor combinations of Planet, Sentinel 1, Sentinel 2 map field-level tillage practices of smallholder farms?
2. Does improved spatial, temporal, or spectral resolution lead to greater increases in accuracy?
3. Can we use only early season imagery to effectively map tillage practices, which can be used to provide within-season maps of ZT adoption?

This study is one of the first to examine how well tillage practices can be mapped in smallholder systems using newer high-resolution satellite imagery. While the analyses presented in this paper are specific to our study area in India, it is likely that the broad findings found in our study can be used to inform the most effective ways to map tillage practices in other smallholder systems across the globe.

2. Method
2.1 Study area

The study was conducted in Arrah district, Bihar, India (25.47°N, 84.52°E) during the winter growing season in 2017 (Figure 1). Bihar is endowed with good soil and a high amount of rainfall, but its agricultural productivity is one of the lowest among Indian states (Bihar 2008). Although the adoption of ZT technology in Bihar is increasing through time, it is still limited

because many farmers lack awareness of ZT and do not have access to machinery required for ZT (Keil, D'souza, and McDonald 2017).

We focused on a 30 by 70 km^2 region where there was variation in tilling practices, and we collected ground truth data from 20 villages distributed across the study area. This region is predominantly comprised of smallholder agriculture (< 2 ha), with farms covering over 80% of land area and with over 80% of the region's population taking part in farming (Salam, Anwer, and Alam 2013). There are two main cropping seasons in this region, the monsoon (*kharif*) season, which spans from June to October and is when most farmers plant rice, and the winter (*rabi*) season, which spans from November to April and is when most farmers plant wheat (Jain et al. 2016). Our study only focused on wheat fields planted during the winter cropping season. The sowing dates of wheat vary widely across the study region from mid-November to late December, and harvest dates largely occur in early to mid-April (Newport et al. 2020).
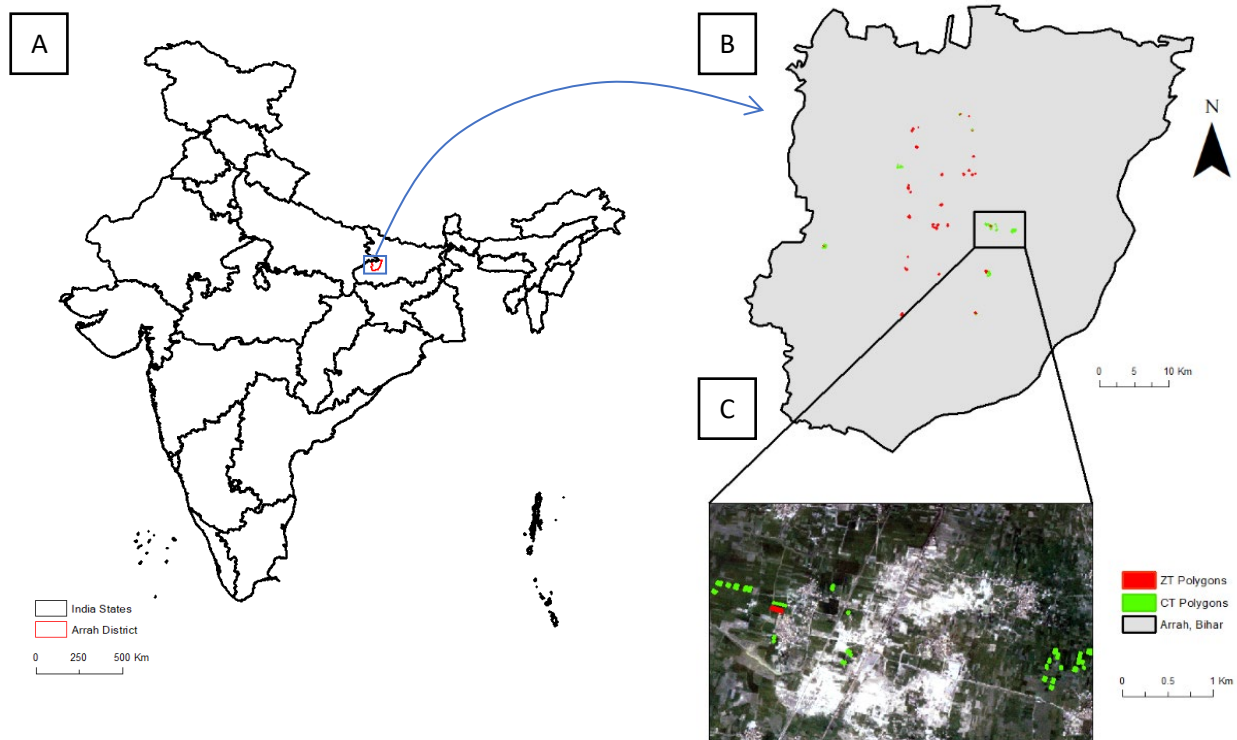

Figure 1. Maps showing (A) the location of our study area in India, (B) our study polygons plotted in Arrah district, Bihar and (C) a zoom in of our polygons overlaid on Planet imagery

2.2 Field Data Collection and Polygon Digitization

Ground truth data were collected during October 2017 by field staff from the Cereal Systems Initiative of South Asia (CSISA). The survey collected information on tillage practices, including whether the field was CT or ZT, and residue for each field (See Appendices Table 1). In addition, we collected GPS locations at the four corners and at the center of each field which were later used to manually digitize field boundaries. We did this by overlaying all GPS points on high-

resolution imagery in Google Earth Pro and manually drew polygons that connected the four corner GPS locations. We then adjusted these polygons to match visible field boundaries that we could see in the high-resolution imagery. We selected the image date within Google Earth Pro that was closest to our time of survey to ensure that visible field boundaries in the imagery were consistent with the field boundaries that we surveyed on the ground. Our survey data were collected from a total of 160 fields, with 65 fields representing ZT and 95 fields representing CT.

2.3 Satellite Data and Pre-processing

We selected the time period for our analysis by considering the timing of cropping cycles in this region as well as the phenologies of ZT and CT fields (Figure 2). Considering the timing of cropping cycles, wheat was planted in our study area from November 11 to December 31, with tillage occurring from mid-October to early November. To ensure that we captured the full range of when the field was fallow prior to planting wheat, we used October 1st as the first date of our study period. Considering NDVI (normalized difference vegetation index) phenologies, we observed that NDVI values became very similar after mid-February for fields that used the two tillage practices (Figure 2). Thus, we used March 1st, 2018 as the last date of our study period. We defined the sowing season as October 1 to December 31, since this time period spanned the full range of sowing dates in our dataset.
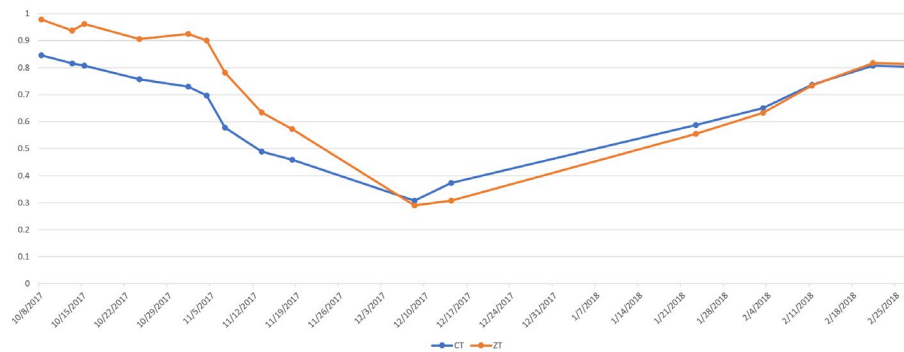

Figure 2. Phenology curves generated from averaged NDVI values of all ZT and CT fields for the 2017-18 growing season using Sentinel-2 imagery.

To analyze the how effectively higher-resolution, readily-available satellite imagery could map smallholder tillage practices, we used images from three different satellite sensors: 1) Synthetic Aperture Radar (SAR) Sentinel-1 (Torres et al. 2012), 2) multi-spectral Sentinel-2 (Drusch et al. 2012), and 3) multi-spectral PlanetScope (Marta 2018). We obtained Sentinel-1 and Sentinel-2 data through Google Earth Engine (GEE) (Gorelick et al. 2017) and PlanetScope imagery through the Planet API (Marta 2018).

We obtained 13 Sentinel-1 C-band Level-1 Ground Range Detected images during our study period (Table 1). They were acquired on a descending orbit in Interferometric Wide swath mode (IW). Prior to ingestion into GEE, the data were preprocessed using the Sentinel-1 Toolbox (Luis et al. 2014). Since speckle filtering was not done prior to ingestion, we implemented speckle filtering using the Refined Lee speckle filter code developed by Guido Lemoine

(https://code.earthengine.google.com/2ef38463ebaf5ae133a478f173fd0ab5) and converted backscatter values to decibels using a logarithmic transformation. The bands and indices we used from Sentinel-1 are shown in Table 2. The intensity cross-ratio (CR) VV/VH was included as previous studies have shown that it is helpful for differentiating vegetation types (Vreugdenhil et al. 2018). We resampled all Sentinel-1 images to 3 m resolution to match fine-scale PlanetScope data using bilinear interpolation in GEE.

Table 1. List of acquisition dates of satellite images used in our study

Dataset	Sentinel-1	Sentinel-2	PlanetScope
Sowing season	10/03/2017	10/08/2017	10/08/2017
	10/15/2017	10/23/2017	10/13/2017
	10/27/2017	10/28/2017	10/15/2017
	11/08/2017	11/12/2017	10/24/2017
	11/20/2017	11/22/2017	11/01/2017
	12/02/2017	12/02/2017	11/04/2017
	12/14/2017	12/12/2017	11/07/2017
	12/26/2017		11/13/2017
			11/18/2017
			12/08/2017
			12/14/2017
	01/07/2018	01/31/2018	01/23/2018
	01/19/2018	02/05/2018	02/03/2018
	01/31/2018	02/15/2018	02/11/2018
	02/12/2018	02/20/2018	02/21/2018
	02/24/2018		02/27/2018

We obtained 11 Sentinel-2 Level-1C Top-Of-Atmosphere (TOA) scenes from GEE during our study period (Table 1). We only selected images that had less than 10% cloud cover, and visually inspected all selected images to ensure that there was no cloud cover over our field polygons. We then applied surface reflectance (SR) correction to all tiles using the radiative transfer emulator Second Simulation of the Satellite Signal in the Solar Spectrum (6S) (Wilson 2013). The 6S algorithm generates interpolated look-up tables (LUTs) under different atmospheric conditions, considering solar zenith, ozone, and surface altitude. These LUTs are then used to calculate atmospheric correction coefficients which convert TOA radiance to SR. The bands and indices that we used from Sentinel-2 are shown in Table 2. We did not consider bands B1, B9 and B10 because these bands represent atmospheric features, including aerosols, water vapor, and cirrus, and are not measures of the surface reflectance of land features. We computed eight spectral indices that were shown to help differentiate vegetation and/or tillage practices in the previous literature (Table 2). We resampled all Sentinel-2 images to 3 m resolution to match fine-scale PlanetScope data using bilinear interpolation in GEE.

We obtained 16 low-cloud Level-3B surface reflectance PlanetScope images (Table 1) that had been atmospherically corrected using the 6S radiative transfer model with ancillary data from MODIS (Anon n.d.). We defined low-cloud images as those with less than 5% cloud cover, and we further visually inspected all filtered images to ensure that there was no cloud cover over our field polygons. We mosaicked all individual image tiles from the same date using color matching of the overlapping regions using the raster package in R Project Software (Team 2013). Previous

studies have shown that there are still inaccuracies in SR correction in the Level-3B product (Houborg and McCabe 2018). Thus, we conducted additional SR correction by histogram matching PlanetScope data and Sentinel-2 imagery using methods from Jain et al (Jain et al. 2016). The bands and indices that we used from PlanetScope are shown in Table 2. We computed the same indices as those calculated from Sentinel-2 using the red, green, and NIR bands (Table 2).

Table 2. Band and index information for the three sensors used in this study

Sensor	Spectral Index & Band	Description (Mean Wavelength: µm)	Reference
Sentinel-1	VV	vertical transmit/vertical receive	
	VH	vertical transmit/horizontal receive	
	CR	Log ratio of (VV/VH)	(Vreugdenhil et al. 2018)
Sentinel-2	B1 – not used	Coastal Aerosols (0.443)	
	B2	Blue (0.490)	
	B3	Green (0.560)	
	B4	Red (0.665)	
	B5	Red Edge 1 (0.705)	
	B6	Red Edge 2 (0.740)	
	B7	Red Edge 3 (0.783)	
	B8	NIR (0.842)	
	B8A	Red Edge 4 (0.865)	
	B9 – not used	Water Vapour (0.945)	
	B10 – not used	Cirrus (1.375)	
	B11	SWIR 1(1.610)	
	B12	SWIR 2 (2.190)	
	NDTI	(SWIR1 – SWIR2) / (SWIR1 + SWIR2)	(Peña-Barragán et al. 2011)
	CRC	(SWIR1 – Green) / (SWIR1 + Green)	(Sullivan et al. 2006)
	NDVI	(NIR - Red) / (NIR + Red)	(S. Fletcher 2016)
	GCVI	(NIR / Green) − 1	(Gitelson et al. 2003)
	OSAVI	(NIR - Red) / (NIR + Red + 0.16)	(Steven 1998)
	NDI5	(NIR - SWIR1) / (NIR + SWIR1)	(Peña-Barragán et al. 2011)
	NDI7	(NIR – SWIR2) / (NIR + SWIR2)	(Peña-Barragán et al. 2011)
	STI	SWIR1 / SWIR2	(van Deventer et al. 1997)
PlanetScope	B1	Blue (0.485)	
	B2	Green (0.545)	
	B3	Red (0.630)	
	B4	NIR (0.820)	
	GCVI	(NIR / Green) − 1	(Gitelson et al. 2003)
	OSAVI	(NIR - Red) / (NIR + Red + 0.16)	(Sullivan et al. 2006)
	NDVI	(NIR - Red) / (NIR + Red)	(S. Fletcher 2016)

2.4 Random Forest Classification

We used random forest (RF), an ensemble-based algorithm, to classify ZT versus CT fields. To ensure even representation in our training data regardless of field size, we randomly sampled twenty pixels from each field; for fields that were smaller than twenty pixels, we considered all available pixels within that field. In addition, we ensured an equal ratio between ZT and CT fields in both our training and validation datasets. To reduce the effect of multicollinearity on our analyses given the large number of features considered in our models, we removed highly correlated features ($r > 0.9$) using the caret package in R Project Software (Kuhn 2008). We set the number of trees for RF parameters as 500 and the number of features as $\sqrt{p}$, where p equals the number of features in the dataset. All RF classifier operations were run using the package randomForest in R Project Software (Ayyadevara 2018). The input datasets for all seven models for sowing season and full season analyses are shown in Table 3.

Table 3. Feature components of different sensor and sensor combinations and full and sowing season models

Model	Sensor & Sensor combinations	No. of Features	No. of Selected Features	Feature Components
Full Model	Sentinel-1	39	15	(2 bands + 1 index) × 13 dates
	Sentinel-2	198	56	(10 bands + 8 indices) × 11 dates
	Planetscope	112	34	(4 bands + 3 index) × 16 dates
	Sentinel-1 + Sentinel-2	237	61	(2 bands + 1 index) × 13 dates + (10 bands + 8 indices) × 11 dates
	Sentinel-1 + Planetscope	151	45	(2 bands + 1 index) × 13 dates + (4 bands + 3 index) × 16 dates
	Sentinel-2 + Planetscope	310	77	(10 bands + 8 indices) × 11 dates+ (4 bands + 3 index) × 16 dates
	Sentinel-1+ Sentinel-2 + Planetscope	349	88	(2 bands + 1 index) × 13 dates + (10 bands + 8 indices) × 11 dates+ (4 bands + 3 index) × 16 dates
Sowing Model	Sentinel-1	24	11	(2 bands + 1 index) × 8 dates
	Sentinel-2	126	38	(10 bands + 8 indices) × 7 dates
	Planetscope	77	25	(4 bands + 3 index) × 11 dates
	Sentinel-1 + Sentinel-2	150	41	(2 bands + 1 index) × 8 dates + (10 bands + 8 indices) × 7 dates
	Sentinel-1 + Planetscope	101	30	(2 bands + 1 index) × 8 dates + (4 bands + 3 index) × 11 dates
	Sentinel-2 + Planetscope	203	49	(10 bands + 8 indices) × 7 dates+ (4 bands + 3 index) × 11 dates
	Sentinel-1+ Sentinel-2 + Planetscope	222	55	(2 bands + 1 index) × 8 dates + (10 bands + 8 indices) × 7 dates+ (4 bands + 3 index) × 11 dates

We evaluated our model using boostrapping, where 70% of field polygons were used for model training and 30% of field polygons were used for model validation. We conducted the bootstrap analysis for 400 iterations as previous work has shown this leads to results with a 95% confidence level (Davidson and MacKinnon 2000).

2.5 Impact of spatial, temporal, and spectral resolution

To better understand the effect of improved spatial, temporal, or spectral resolution on classification accuracies, we conducted analyses that examined the individual contribution of each in our models. First, to assess the contribution of spatial resolution on classification accuracies, we resampled the spatial resolution of Planet (3 m) to 10 m to match the spatial resolution of Sentinel-2 imagery using bilinear interpolation in GEE. We reran our single sensor Planet model using the aggregated, coarser resolution (10 m) data, and compared model results with those from the model using the original Planet data (3 m). Second, to identify the impact of improved temporal resolution on classification accuracy, we reduced the number of images used in our Planet analysis to only those dates that were similar to those available with Sentinel-2 data (Table 1). We then reran our single sensor Planet model using these limited dates (7 dates), and compared the results of this model with those from the original Planet model that included all available image dates (11 dates). Finally, to assess the impact of increased spectral information on classification accuracies, we reduced the number of bands and indices used in the single sensor Sentinel-2 model to match those used in the single sensor Planet model. We then reran our single sensor Sentinel-2 model using these limited spectral bands and indices (7 bands and indices), and compared the results of this model with those from the original Sentinel-2 model that included all available bands and indices (18 bands and indices). We only conducted these analyses using the sowing period data and compared results to those obtained using the original sowing period models.

3. Results

Considering which sensor and sensor combinations led to the highest classification accuracy (Research Question 1), we found that for single sensor models, PlanetScope led to the best performing model for both the sowing period and full period models. The Planet model obtained accuracies that were 3-5% higher than the next best performing single sensor model that used Sentinel-2 data. Findings indicated that the model that used only Sentinel-1 data performed poorly, with accuracies at least 20% lower than models using Sentinel-2 or Planet. We found that combining Sentinel-2 data and Planet data led to higher accuracies than individual sensor models, though this two-sensor model had an increase in accuracy of only 1% compared to the Planet model. We found that adding Sentinel-1 data did little to improve classification accuracy, and in many cases reduced overall accuracy compared to individual sensor models that used Sentinel-2 or Planet imagery. Finally, we found that the highest classification accuracy in both the sowing period and full period models were obtained with the three-sensor model. The accuracies of the three sensor models, however, were only 1% better than the single sensor model that used Planet data.

Considering whether using only images from the sowing period could lead to high classification accuracies (Research Question 2), we found that models that used only image dates from the sowing period obtained accuracies that were very similar to the full season model, usually within a 1% difference. This was especially true for the models that included PlanetScope either in single or multi-sensor models. The biggest difference between the sowing versus full period models were seen for models that used Sentinel-2 data, with overall accuracies decreasing by approximately 3% for the sowing date model compared to the full model. These results suggest

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that using only images during the sowing season is as effective as using images throughout the growing season in mapping tillage practices in this region.

Table 4. Classification results for single and multiple sensor models during the sowing period (Oct - Dec) and full study period (Oct - Mar)

Sensor & Sensor combinations	Sowing Model Overall Accuracy	Full Model Overall Accuracy
Sentinel-1	61.24%	62.28%
Sentinel-2	80.8%	83.24%
PlanetScope	85.78%	86.55%
Sentinel-1 + Sentinel-2	79.95%	82.65%
Sentinel-1 + PlanetScope	86.03%	86.39%
Sentinel-2 + PlanetScope	86.93%	87.61%
Sentinel-1 + Sentinel-2 + PlanetScope	86.84%	87.71%

Finally, considering the impact of improved spatial, temporal, and spectral resolution (Research Question 3), we found that the model that used Planet satellite data aggregated to 10 m resolution led to a reduction in accuracy of 4.5% compared to the original Planet model using 3 m resolution data (Table 5). This result suggests that improved spatial resolution (3 m vs 10 m) moderately increases the accuracy of mapping field-level tillage practices. Considering temporal resolution, we found that the model that used 7 Planet scenes had a reduction in accuracy of 2% compared to the Planet model that used all 11 available scenes (Table 5). This result suggests that increased temporal resolution from Planet plays a minor role in improving accuracies. Finally, considering spectral resolution, we found that the model that used Sentinel-2 data with only the bands and indices available with Planet led to a reduction in accuracy of 0.5% compared to the original Sentinel-2 model (Table 5). This result suggests that the increased spectral resolution of Sentinel-2 does not play a significant role in mapping field-level tillage practices.

Table 5. Classification results for low and high spatial, temporal, and spectral resolution models

Changing Resolution	Low Resolution Model Overall Accuracy	High Resolution Model Overall Accuracy
Spatial	81.32% (Planet images aggregated to 10 m)	85.78% (Planet images at 3 m)
Temporal	84.55% (7 Planet scenes)	86.55% (11 Planet scenes)
Spectral	80.17% (Sentinel-2 images with 7 bands and indices)	80.8% (Sentinel-2 images with 18 bands and indices)

4. Discussion and Conclusion

Our study examined which satellite sensor and sensor combinations as well as time periods resulted in the highest classification accuracies for mapping tillage practices for smallholder farms in Bihar, India. We found that models that included Planet data led to the highest classification accuracies, and that models that included Sentinel-1 led to the lowest classification accuracies.

Though previous studies have found that using multiple sensors can lead to higher classification accuracies, we found that the best performing two sensor model and three sensor model only improved accuracies by approximately 1% compared to models that only used Planet data. This suggests that in the case of smallholder farms, Planet data alone may be able to effectively map tillage practices, at least during dry growing seasons with limited cloud cover. Considering time periods, we found that the models built using only data during the sowing period were as effective as models that used data throughout the growing season. This suggests that it may be possible to map tillage practices with high accuracy after sowing has ended, providing the ability to produce real-time, within season maps of zero tillage practices at scale. Our results broadly show that tillage practices can be mapped with high accuracy (> 86%), even in heterogeneous, smallholder systems when using relatively new high-resolution, readily available satellite imagery.

We believe that the main reason Planet performed better than additional sensors is due to its higher spatial resolution. This is because our analyses that examined the individual effect of improved spatial, temporal, and spectral resolutions found that reduced spatial resolution led to the greatest change in model accuracies (4.5% compared to $\leq$ 2%). The reason improved spatial resolution is likely important for model accuracy is because Planet's improved spatial resolution of 3 m leads to fewer mixed pixels than when using coarser Sentinel-2 imagery (10 m resolution; Figure 3) given the small size of fields within our study region (< 0.3 ha). Interestingly, even though PlanetScope has improved temporal coverage as well compared to Sentinel-2, this increased temporal availability improved model accuracy only modestly (2 %), despite more than doubling the number of images available. Sentinel-2 data led to models with moderate accuracy, though these models were only ~5% lower in accuracy compared to Planet models. Overall we found that Sentinel-1 led to low classification accuracies and did little to improve multi-sensor model accuracies; these results are similar to those found by Azzari et al. [4], which mapped tillage practices across the United States Midwest.
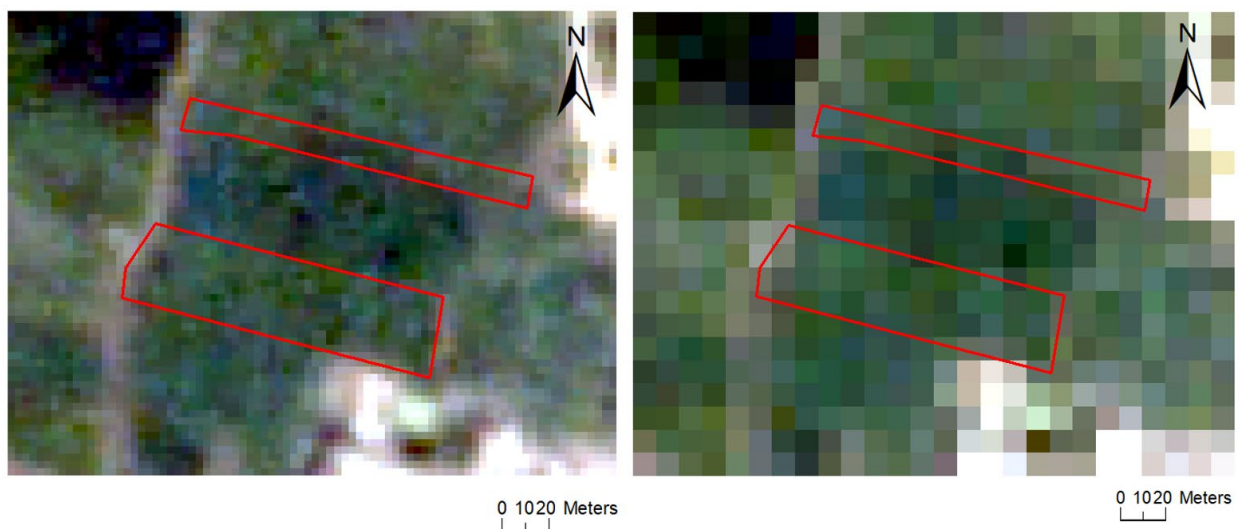

Figure 3. (A) PlanetScope Image (3 m) and (B) Sentinel-2 Image (10 m)

Interestingly, we found that models that relied on using data only from the sowing season had similar accuracies to models that used data from the full study period. This suggests that the factors that are most important for distinguishing between ZT and CT likely occur during the field-

preparation and sowing periods. Mechanistically this makes sense given that ZT fields are often covered in crop residue in this region, while CT fields are often bare. This is because under ZT, farmers do not till the soil and can plant wheat seeds within remaining rice residue. This remaining residue may lead to higher NDVI values in ZT fields compared to CT (Figure 2) due to remaining green vegetated biomass from the prior rice harvest (Daughtry et al. 2005).

There are several limitations of our study. First, we predicted only a binary variable of ZT versus CT, instead of a continuous variable representing tillage intensity. In reality, farmers who practice CT have heterogeneous management, with farmers varying the number of times they till their fields. Previous studies have found that it is possible to accurately classify tillage intensity of large-scale farms (Azzari et al. 2019),and future work should explore whether this is also possible in smallholder systems. Second, we conducted our study during the largely dry winter growing season which has limited cloud cover compared to India's main growing season during the monsoon. It is possible that which sensor(s) lead to the highest classification accuracies may differ during cloudy seasons where optical image availability is more limited. Previous studies, for example, have shown that Sentinel-1 becomes more important for improving classification accuracies during periods of high cloud cover when optical imagery is unavailable. This is largely because studies have shown that Sentinel-1 C-band data can appropriately detect vegetation phenologies across a wide range of land-cover types (Song and Wang 2019; Supriatna 2019), and our data suggest that ZT versus CT fields have distinct vegetation phenologies (Figure 2), particularly during the early part of the growing season. Finally, our study is limited in spatial and temporal scale; future work should examine how generalizable our findings are to different smallholder farming systems and across time.

In conclusion, we found that it is possible to use readily-available, high spatial resolution satellite data to map tillage practices of smallholder farms. In particular, Planet satellite data resulted in high classification accuracy models (> 86%) and including data from additional sensors did little to improve accuracies. Tillage practices can also be mapped effectively using only data from the period of sowing, suggesting that real-time, within season maps of tillage can be produced at scale. Our work highlights the important role of micro-satellite data to map agricultural characteristics of smallholder farms, which is exciting given that the temporal resolution of such imagery is only expected to increase over the coming years as additional satellites are launched.

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Appendices

Table S1. Crop Residue & Soil Till Information (Only collect this information for wheat plots)

	Did you till the soil before planting wheat?	Yes No
If yes:	How many days before seeding wheat did you till your field?	
	What did you use to till your soil (circle all applicable choices)?	Rotovator Plough/Harrow Planking Other _____
	What was the number of passages you used for each method?	Rotovator _____ Plough/Harrow _____ Planking _____ Other _____
	What type of tractor did you use to till your soil?	My own tractor Rented tractor Other _____
	Did you irrigate your wheat plot before sowing?	Yes No
If yes:	How many days before seeding did you irrigate your wheat?	
	Which crop was grown before wheat seeding?	
	How was this previous monsoon crop harvested?	Manual Combine Other _____
	How was the previous monsoon crops' residue managed?	Collected Burnt Other _____
	What crop will you plant in this plot during the upcoming monsoon season?	
	Will you till the soil before planting this monsoon crop?	Yes, I already tilled Yes, I will till later No, I will not till
If yes:	Will you do puddling before planting the monsoon crop, and is it deep or light?	Yes, I do deep puddling Yes, I do light puddling No, I do not do puddling