Mapping smallholder forest plantations in Andhra Pradesh, India using multitemporal Harmonized Landsat Sentinel-2 S10 data

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Abstract

This study's objective was to develop a method by which smallholder forest plantations can be mapped accurately in Andhra Pradesh, India, using multitemporal visible and near-infrared (VNIR) bands from the Sentinel-2 MultiSpectral Instruments (MSIs). Conversion to agriculture, coupled with secondary dependencies on and scarcity of wood products, has driven the deforestation and degradation of natural forests in Southeast Asia. Concomitantly, forest plantations have been established both within and outside of forests, with the latter (as contiguous blocks) being the focus of this study. Accurately mapping smallholder forest plantations in South and Southeast Asia is difficult using remotely sensed data due to the plantations' small size (average of 2 hectares), short rotation ages (4-7 years for timber species), and spectral similarities to croplands and natural forests. Cloud-free Harmonized Landsat Sentinel-2 (HLS) S10 data was acquired over six dates, from different seasons, over four years (2015-2018). Available *in situ* data on forest plantations was supplemented with additional training data resulting in 2,230 high-quality samples aggregated into three land cover classes: nonforest, natural forest, and forest plantations. Image classification used random forests on a thirty-band stack consisting of the VNIR bands and NDVI images for all six dates. The median classification accuracy from the 5-fold cross-validation was 94.3%. Our results, predicated on high-quality training data, demonstrate that (mostly smallholder) forest plantations can be separated from natural forests even using only the Sentinel-2 VNIR bands when multitemporal data (across both years and seasons) are used.

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Short Running Title: Sentinel-2 forest plantation mapping

Keywords: remote sensing, random forest, NDVI, trees outside forests, machine learning, classification

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1. Introduction

Conservation of the world's forests has a renewed importance amid both climate and land use changes, particularly in tropical ecosystems across the world. There is demand for highly accurate spatiotemporal quantifications of global forest cover. However, current global models and many studies fail to distinguish between natural and planted forest types, thus altering the true measure of forest area (Anil, 2011; Hansen *et al*., 2013; Kayet and Pathak, 2015; Puyravaud *et al*., 2010). Separation of forest types is imperative considering the differences of ecological and socio-economic utility among planted and natural forests (Koskinen *et al*., 2019).

The critical importance of ecosystem services provided by planted forests will increase in the future due to new opportunities in a globalized market attributed to improvements in wood products and processing technologies. Sustainable and intensively managed planted forests continue to support the growing demand for forest products from timber and wood fiber to oils and fruits (Peterson *et al*., 2016). In addition to the products extracted from trees, plantations support several external ecosystem services such as clean water, carbon sequestration, regulation of the hydrological cycle, connectivity of habitat fragmentation for biodiversity conservation, and mitigation for deforestation (Kanninen *et al*., 2010).

Accurate mapping of trees outside forests is important both economically and scientifically. Expansion of forest area has been identified as a possible natural climate solution (Griscom *et al*., 2017), and accurate carbon accounting will require quantification of trees outside forests as well as those in greenwash areas. Plantation establishment and forest degradation both affect radiative forcing through changes in albedo and biosphere-atmosphere gas exchange. While not a focus of this study, improved monitoring of conditions of native forests can assist in estimation of biodiversity richness and habitat fragmentation (Roy *et al*., 2013).

Difficulties in separating natural from managed forests are further exacerbated by a certain degree of definitional differences within the scientific community as to what, precisely, is considered a forest. This is due to a number of factors, including whether forests are being defined as a land use or a land cover, how society interacts with the forest, and the wide diversity of forest ecosystems around the world. Because of this, the Food and Agriculture Organization Global Forest Resources Assessment of 2000 (FAO FRA) compiled over 650 definitions of forests used in developing countries, and attempted to reduce these definitions into a set of global forest classes that could be applied more consistently (FAO 2001), while still enabling some national modifications where appropriate. This enables comparison of trends in forest cover across nations, and a periodic global accounting of forest cover. As defined by for the FAO FRA 2015, a forest is land spanning over 0.5 ha with tree height above 5 meters and a 10% or more canopy cover, or trees that can meet these thresholds *in situ*. FAO's definition of forest excludes tree stands in an agricultural production system like fruit tree plantations, oil palm plantations, olive orchards, and other agroforestry systems. Their definition of planted forest is "forest predominantly composed of trees established though planting and/or deliberate seeding." In the 2017 Forest Survey of India, the forest class consists of very dense, moderately dense, and open forest including mangrove cover. However, the land use type "land under miscellaneous tree crops and groves" is not considered as part of the recorded forest area and small plantations are considered "trees outside forests" if they fall outside established mapped greenwash areas. Given the prevalence of plantations on small land holdings, this definitional exclusion has led to a differential estimation of tree cover in some regions from both the FAO and Forest Survey of India definitions, which has implications for carbon accounting and the monitoring of other ecosystem services in India.

In Southeast Asia, smallholder forest plantations have gained popularity and are replacing degraded or unproductive crop land, offsetting the demand on primary forests (Binkley, 2003; Okarda *et al*., 2018; Puyravaud *et al*., 2010; Roy *et al*., 2015; Rudel, 2009). Clonal plantations are common in planted forests to genetically improve the growing stock and produce a fast, high yield stock of species such as *Eucalyptus globus* and *Casuarina spp.* (Sharma *et al*., 2018). Also, palm tree species, notably oil palm and coconut, have rapidly expanded across Southeast Asia due to global market demand (Kannan *et al*., 2017; Putra *et al*., 2019). Smallholder farmers, local people in the rural tropics cultivating personal land for subsistence and commercial purposes, are known for their self-initiated forest plantation establishment on plots from one to a few hectares (Pokorny *et al*., 2010). Paper industries are also seeking available waste and barren land for forest plantation establishment (Rudel, 2009; Sharma *et al*., 2018). This land-use conversion (from marginal agricultural land to forest plantation) can reduce the exploitation of primary natural forests (Paquette and Messier, 2010).

Multitemporal and multispectral remote sensing data have been widely used for land use and land cover mapping through utilization of relationships between reflectance and vegetation. However, accurately mapping forest plantations in Southeast Asia using remotely-sensed data has been historically constrained by the following: (1) many plantations are small (averaging 2 ha) relative to widely available moderate resolution earth resource satellite data (Lechner *et al*., 2009), (2) rotation ages for fiber plantations are short (often just 4-7 years) (Sharma *et al*., 2018), (3) newly established or recently harvested plantations are particularly difficult to identify correctly (FSI, 2013), and (4) the surrounding cropland area is variegated in both time and space. Spatial resolution has been one of the main limitations to mapping smallholder forest plantations. Furthermore, while plantations have the potential to be spectrally similar to some agricultural land uses (Griffiths *et al*., 2019) and natural forest (Behera *et al*., 2001), they are harvested less frequently than crops, but nonetheless on a regular cycle. A natural forest, in contrast, experiences seasonality but (typically) no harvest. The temporal differences between these two forest types appear tailor-made for interannual multitemporal analysis of remotely sensed data.

On satellite imagery the canopy of a mature forest plantation looks visually similar to a natural forest and a young plantation appears similar to many crop types. All vegetative land use and land cover types act very differently across time, and current models fail to differentiate smallholder forest plantations from natural forest and cropland (Anil, 2011; Hansen *et al*., 2013; Kayet and Pathak, 2015; Reddy *et al*., 2016b). Different approaches to mapping forest plantations have tradeoffs considering the wide variety of freely available remotely sensed data and land use and cover modeling algorithms. MODIS has been commonly used in land use and land cover analysis due to the high frequency of image acquisitions, although a significant limitation is the spatial resolution (250 m) that does not permit detection of smallholder forest plantations, shifting focus to only large-scale plantations. Remotely sensed data has been used across numerous studies for forest plantation mapping using optical imagery from Landsat (Coleman *et al*., 1990; Nooni *et al*., 2014; Kayet and Pathak, 2015; Peterson *et al*., 2016) and MODIS (le Maire *et al*. 2011; Miettinen *et al*., 2012; Jia *et al*., 2016). There has also been a large body of work in which optical imagery was fused with radar data from ALOS PALSAR (L-band) or Sentinel-1 (C-band; Pin Koh *et al*., 2011; Tobrick *et al*., 2016; Koskinen *et al*., 2019; Poortinga *et al*., 2019). Peterson *et al*., (2016) tabulate previous studies mapping forest plantations (mainly oil palm), including their methods, imagery, and accuracy percentages. The two with the highest accuracies (albeit with no focus on smallholders) use a supervised decision tree classifier with 30 m Landsat imagery (Miettinen *et al*. 2012; Nooni *et al*., 2014).

Except for oil palm (because of the characteristic backscatter response of palm canopies; Descals *et al*., 2019), there is often little synergism to be gained from combining optical and radar data for tree plantation detection. Mercier *et al*. (2019) used Sentinel-1 and Sentinel-2 data (each alone and in combination) to map seven classes (bare soils, artificial surfaces, water bodies, forested areas, croplands, pastures, and secondary forests) in forest-agriculture mosaics in Spain (temperate) and Brazil (tropical). The maps produced using the optical (Sentinel-2) data were superior to those produced using the radar (Sentinel-1) data with respect to classification accuracy. However, the combination of the two data sources yielded a very slight increase in classification accuracy over the optical data alone only for the temperate site. In the tropics, there was no statistical difference between the classification accuracies that used the combined dataset versus use of the optical data alone. As such, it appears that Sentinel-2 data are an excellent choice for the classification of forest-agriculture mosaics in the tropics.

The National Remote Sensing Centre (NRSC) in India produces a periodic land cover classification model for the Forest Survey of India (FSI) using LISS-III data (23.5 m spatial resolution). Their current classification protocol uses satellite imagery from October to December using the green, red, NIR, and SWIR bands. Post monsoonal data is optimal, considering low cloud cover and the post monsoonal flush of leaves which enhances detection of the vegetation types. Identified limitations to forest plantation detection in this assessment include the following: low spatial resolution compared to the average plantation size, non-availability of appropriate seasonal data, mixed classes with forest areas adjacent to cropland, young plantations and trees with less chlorophyll due to low leaf area index and transmittance, and high heterogeneity of tree species (FSI, 2017).

Tree cover in the FSI consists of forest patches less than one hectare in extent that are outside the recorded forest area (FSI, 2019). Tree cover is enumerated using a stratified random sampling approach (with a panel design in which grids are apportioned to a given survey year). Sentinel-2 VNIR data are used to identify linear and block forest plantations as well as scattered trees (which become the strata) in the chosen sample grids. A random sample of points is chosen from each stratum for field verification and inventory. This robust methodology has a reported standard error of the estimate of just 6% (FSI, 2019). There are substantial differences from state to state however, ranging from under 4% in Gujarat to over 14% in Arunachal Pradesh, constrained by (1) the accuracy with which forest plantations are mapped in the first instance and (2) the representativeness of the grids for each biennial assessment and state. High-accuracy wall-to-wall identification of FSI tree cover strata would likely improve statistical efficiency of the tree cover estimates.

Because of their inherent suitability Sentinel-2 data have been used in a few studies to map nonindustrial forest plantations, primarily those producing non-timber forest products. Descals *et al*. (2019), as earlier noted, were able to successfully identify smallholder palm plantations in Sumatra using a combination of Sentinel-1 and Sentinel-2 data. Nomura and Mitchard (2018) used Sentinel-2 data alone (all 10-20 m bands plus NDVI and the standard deviation of NDVI) from images acquired in February, 2017; February, 2018; and March, 2018 to separate forest plantations (oil palm, rubber, and betel nut; no timber species) from natural forest and nonforest land uses in Myanmar. Smallholdings, on average, are larger in Myanmar (2-5 ha) than in India (under 2 ha) (Lowder *et al*., 2016; Nomura and Mitchard, 2018) enabling use of the reduced 20 m resolution. Mercier *et al*. were able to map secondary forest (including forest plantations) using a 'single-date' mosaic (with acquisitions only 12 days apart) using all 10-20 m Sentinel-2 bands. The use of the SWIR bands was again feasible because of very large agriculture holdings (20-100 ha.; Nomura and Mitchard, 2018). With the exception of FSI mapping of tree cover strata, to our knowledge no prior effort has used multitemporal VNIR data to map the very small forest plantations, comprised in part of timber species, that exist outside greenwash areas in India.

High spatial resolution data are clearly needed. However, while licensed very high spatial resolution data are available from numerous commercial or state entities, only Sentinel-2 VNIR data, at 10 m resolution, have strong potential for smallholder plantation mapping at no cost for the data. Sentinel-2 VNIR data are widely used in land cover and land use change (LCLUC) science for vegetation mapping (Immitzer *et al*., 2016; Pesaresi *et al*., 2016; Thanh Noi and Kappas, 2017; Belgiu and Csillik, 2018; Khaliq *et al*., 2018; Jin *et al*., 2019), but, as noted above, SWIR bands are commonly used by FSI and other entities to separate plantations from other land uses. However, use of multitemporal data to capture spectral variability across seasons (e.g., Poortinga *et al*., 2019) and years has the potential to obviate the challenges associated with use of the VNIR data alone.

The objective of this study was to develop a method by which smallholder forest plantations can be mapped accurately in Andhra Pradesh, India using multitemporal (intra- and inter-annual) visible and near-infrared (VNIR) bands from Sentinel-2.

2. Study Area

In this study we focus on the two districts in Andhra Pradesh, India surrounding the Godavari River: East Godavari and West Godavari (See Figure 1). The total area is of both districts combined is 18,501 km^2 and it is located in the southeast region of India between 16^{o}15' N and 18^{o}00' N latitude and 81^{o}00' E 82^{o}20'E longitude. This tropical region experiences three different seasons: winter (October-February), summer (March-June), and monsoon (July-September). During the monsoon season, these districts receive rainfall from the southwest monsoon from June to September, as well as the northeast monsoon through October and into November (Reddy *et al*., 2016a). Rainfall exceeds 1,100 mm during the monsoon season, while only 30 mm of rain can be expected to fall between December and March. The annual average temperature is 31.5 ^{o}C, with the cooler winter months averaging around 28 ^{o}C and the hot, humid summer months reaching 40 ^{o}C (Pike, 2018). The northern part of East and West Godavari is home to the discontinuous hills of India's Eastern Ghats.

With a population of 49.4 million, Andhra Pradesh is prone to population growth furthering urbanization that is expected to exacerbate deforestation. Nevertheless, the region experienced an increase in recorded forest area for the 2017 assessment due to plantation and conservation activities (FSI, 2017; Anil, 2011). Andhra Pradesh's forest cover area in the state, including forest cover within and outside recorded forest area, is 37,258 km^2 which is 22.9% of the total state area (FSI, 2017). The dominant forest types in this region include a majority of southern tropical mixed moist deciduous forests, with some patches of semi-evergreen forests (Aditya and Ganesh, 2018). Between the districts, East Godavari has higher total forest cover at 4,726 km^2. This is due in part to the presence of a natural forest reserve of over 1,000 km^2 in the northern region of the district, known as the Papikondalu National Park (FSI, 2017). At the top of the Eastern Ghats, Papikondalu National Park is known for its densely forested hills, valleys, deep gorges, and streams supplying life to a rich biodiversity of flora and fauna.

3. Materials and Methods

This study applies a commonly used supervised machine learning method, random forests, to map smallholder forest plantations using remotely sensed data. This machine learning approach includes preparation and processing of the satellite imagery, creation of a training and validation dataset, construction and implementation of the classification model, and an assessment of model accuracy. A flow chart illustrating the sequential production and processing of this land cover classification effort is shown as Figure 2.

3.1. Model Implementation Overview

Target (land cover class) and predictor (VNIR reflectances and NDVI for six Sentinel dates) variables were required for training and validation of the random forest classification (Breiman, 1999). The target land cover classes were nonforest, natural forest, and forest plantation. The predictor variables were composited into an image stack of the 30 bands of VNIR and NDVI values from all dates. Training and validation data consisted of 2,230 land cover points. Five-fold cross validation was used for accuracy assessment, in which each fold had 446 samples.

3.2. Harmonized Landsat Sentinel S10

High spatial resolution was a necessity for this study given that the average plantation size is 2 ha. As such, we used the S10 data product from the NASA Harmonized Landsat Sentinel (HLS) program (hls.gsfc.nasa.gov). The S10 product provides Sentinel-2 MultiSpectral Instrument (MSI) imagery in a UTM grid with BRDF-corrected surface reflectance at full resolutions (10 m, 20 m, 60 m) obtained from L1C products processed by the ESA. The term harmonized signifies the use of a common gridding system (resolution, projection, and spatial extent), radiative transfer algorithm to atmospherically correct to surface reflectance (multiplied by 10,000 and represented as a signed 16-bit integer), nadir view geometry normalized by bidirectional reflectance distribution function (BRDF) estimation, and a spectral bandpass adjustment. Along with the atmospheric correction is a series of cloud metrics integrated into the metadata attributes to estimate percent cloud cover for an image (Claverie *et al*., 2018). Sentinel-2 MSI (10 m) was used instead of Landsat 8 OLI (30 m) because its finer spatial resolution was preferable for smallholder forest plantation detection (See Figure 3).

The time at which imagery is acquired plays a key role in land use and land cover classification, considering factors like cloud cover and seasonality of crops (Matton *et al.*, 2015; Morin *et al*., 2019; Nitze *et al*., 2014; Zhang *et al*., 2009). All HLS S10 images covering the study area were acquired from 2015-2018. Our study area covered six of the S10 tiles based on the Sentinel-2 MSI tiling system: T44QNE, T44QND, T44QME, T44QMD, T44QPE, and T44QPD. The data came in the JPG 2000 file type. A MATLAB script was written to convert the files to GeoTIFF format using the image metadata while concomitantly stacking the VNIR (10 m) bands and mosaicking the tiles together. Another MATLAB script sorted through the TIFF files to distinguish images with less than 20% cloud cover using the cloud cover attribute. These images were then visually interpreted in ENVI to select images with zero cloud cover across all tiles. The following dates were chosen: December 28, 2015; November 22, 2016; November 2, 2017; December 22, 2017; March 1, 2018; and June 15, 2018. An NDVI layer was calculated from each of the six HLS images in ENVI using Band Math. NDVI was multiplied by 10,000 and represented as a signed 16-bit integer to correspond with the reflectance representation.

All optical imagery from HLS, plus the six NDVI bands, was combined into a single image stack consisting of 30-bands. Using ERDAS Imagine, the HLS images and NDVI layers were chronologically ordered into a 30-band image stack; five bands across all six dates. Each of the layers in the 30-band image stack were named by band and date (year and day of year). The final image stack was then clipped to a shapefile of the study area.

3.3. Training and validation data

Construction of the training dataset required multiple, extensive random point assessments to achieve complete and clear representation of land cover classes in this region of study, resulting in a final training dataset of 2,230 points aggregated into three main land cover classes: nonforest, natural forest (includes mangroves), and forest plantation (includes palm and pulp wood species) (See Table 1). *In situ* data was collected by our team during several weeks of field work in December 2018. Collaborators from International Paper assisted in identification of forest plantation types in this region. Points were created in ArcMap using the Random Points tool and loaded into Google Earth Pro using available high-resolution imagery (sub-meter resolution from Digital Globe) for visual interpretation. Data quality was insured by multiple analyst data-cleansing procedures in Google Earth Pro to mitigate subjectivity of training classification and identify inconsistent plots with the classification scheme.

Our classification required consideration of the multitemporal nature of the image data and phenological and spectral variability within a main class, therefore photo-interpretation of the high-resolution imagery from Google Earth Pro required the following rules: each point had to be consistently the same sub-class through time (2015-2018), a 10-meter buffer surrounding the point avoided edge pixels, and each point was not mixed with any other subclass. The resulting land cover subclasses include agriculture, aquaculture, ground, sand, urban, shrub/scrub, water, natural forest, mangrove, palm plantations, and forest plantations.

3.4. Connecting spectral response to land cover class predictors

An R script was used to extract the 30 band / NDVI values for each sample point, resulting in a comma-separated values (CSV) file. Each row represented one sample point, and contained the aggregate (target) class, subclass, X location, Y location, and the 30 column reflectance / NDVI vector.

3.5. Separation of vegetation type using NDVI

Vegetation indices (VIs) derived from remotely sensed data enable separation of vegetated from non-vegetated land use and land cover classes. Spectral reflectance is sensitive to photosynthetic activity in the visible and near infrared bands (Morin *et al*., 2019). The normalized difference vegetation index (NDVI) is widely used in forest remote sensing because of its association with leaf area and canopy cover, enabling mapping of forests and their condition (le Maire *et al*., 2011; Nitze *et al*., 2014; Zhu and Liu, 2014). NDVI uses two bands, red and near infrared, in an equation to produce a single value between -1 and 1. The NDVI provides a differencing numerator and a normalizing denominator as shown in equation 1:

$$\frac{NIR - Red}{NIR + Red} \quad \text{(Eq. 1)}$$

Given the similarities in vegetation spectral signatures, the spectral responses from different crop types and natural forest can be confused with planted forests (Morin *et al*., 2019; Nitze *et al*., 2015). NDVI values from a single agriculture and forest plantation (*Casuarina spp.*) training and validation point were graphed across the HLS dates used in the random forest model (See Figure 4). Another analysis using NDVI was performed on all training points included in the two forest type classes: natural forest (mangrove and natural forest) and plantation (fiber and palm plantation). A box plot was implemented to assess the distribution of NDVI values across HLS dates within the two forest type classes (See Figure 5).

3.6. Partitioning and separability of the spectrum

For remote sensing land use and land cover classification, it is good practice to optimize partitioning and separability among predictor and response variables (Campbell and Wynne, 2011). For this study, our predictor variables are the three main land cover classes and the response variables are the spectral responses in the visible and near-infrared bands along with NDVI across all six dates. A feature space image comparing the reflectance responses of the red and NIR bands by land cover class from the first date in 2015 is shown as Figure 6, indicating very good to excellent partitioning. Presence of slight class confusion for the forest plantation class is resolved with use of seasonal and interannual multitemporal data as shown in the canonical plot using all 30 VNIR and NDVI bands (See Figure 7).

3.7. *Random forests*

Multiple machine learning algorithms, including random forests, CART, and SVM, were tested on the dataset. A random forest classifier proved optimal for this large, variegated area. (Pelletier *et al*., 2016) The Julia programming language (version 1.3.0) was chosen for this analysis due to its efficiency and robust memory management. The DecisionTree.jl (version 0.10.0; https://github.com/bensadeghi/DecisionTree.jl) package was used to implement random forests. The classification model used in this analysis includes parameters such as pre-pruning (max depth, min leaf size), post pruning (pessimistic pruning), multi-threaded bagging (random forests), adaptive boosting (decision stumps), and cross validation (n-fold). A random forest with 50 trees was selected after an iterative parameter optimization. Table 2 presents the parameters and descriptions used for our model assessment.

3.8. Accuracy assessment

Model accuracy was estimated from the training and validation dataset using a 5-fold cross-validation, with 446 samples per fold. The error matrix and resulting summary statistics (overall accuracy, kappa, class-specific user’s and producer’s accuracies) were calculated using standard techniques (Campbell and Wynne, 2011).

4. Results

4.1. Classification map

The supervised random forest classifier using the Julia DecisionTree.jl package produced a classification map with 10 m resolution over East and West Godavari separated into 3 land cover classes: nonforest (tan), natural forest (dark green), and forest plantation (light green) (See Figure 8). The nonforest class includes the majority of the land cover classes present in this region and accounted for 74.5% of total area. Natural forest, including conserved forest in the north and mangroves along the coast, is estimated at 14.5% of total area. The target class, forest plantation, includes palm and other tree plantations and amounts to 11% of total area. Model performance was visually assessed at a fine scale using HLS images, classification output, and a high-resolution base map in ArcGIS Pro by zooming into areas with known land use and land cover. Figure 9, for example, shows the result of this process for forest plantations training points in East Godavari. Figure 10 shows another example of the results of the model classification in separating a natural forest area from forest plantations within a cropland forest mosaic in West Godavari. Figure 11 shows the classification output, high-resolution imagery from Google Earth, and HLS images for all land cover classes.

4.2. Accuracy assessment

The validation results are shown using a confusion matrix (See Table 3), and accuracy summary statistics (See Table 4) from the 5-fold cross-validation, 446 samples per fold. As shown in Figures 4 through 7, all utilized dates and bands were important, and iterative, selective elimination of any one date or band produced an evident decrease in model performance. Average overall accuracy across the five folds was 94.3%. The target class, forest plantation, was successfully classified, but was slightly confused with nonforest. The nonforest class had the highest class-specific accuracies, presumably due to its spectral dissimilarity from forest in the aggregate (excluding agriculture) and its preponderance (65.8% of sample points) in the random (but therefore unbalanced) sample.

5. Discussion

Using both intra- (Jia *et al*., 2016) and interannual (Poortinga *et al*., 2019) temporal variation to separate otherwise similar spectral signatures was the cornerstone of this successful classification (see also, e.g., the differences in class separability between Figures 4 and 5). Figure 11 captures the visual spectral variation in false-color HLS image snapshots of different land cover classes compared to the ground reference and model classification. Even a given vegetation type can have different temporal and spectral responses due to differences in local land management, genetic features, site conditions, and many other environmental factors. As such, sampling such that the spectro-temporal feature space is well-partitioned is vital. The use of temporal information enables differentiation of vegetative types using differences in seasonal cycles and vegetation phenology (Griffiths *et al*., 2019; Zhang *et al*., 2009).

Capturing the variability of vegetation phenology (Zhang *et al* 2009) and intra-annual seasonal growing characteristics (Griffiths *et al*., 2019) is essential when modeling the separation of cropland and planted forest types (le Maire *et al*., 2011; Nitze *et al*., 2014). Clear sky observations during the monsoon season are rare to non-existent. As such, the dates used in this analysis include the prominent winter months, where vegetation is at its peak in this region due to water availability, and the summer months to capture vegetation prior to the rainy season when it may be dry or unhealthy. Use of winter and summer dates optimizes separability of vegetation types because the phenology is more stable during these seasons (Morin *et al*., 2019; Behera *et al*., 2001).

The model proved successful in separating forest plantations from agriculture in part using (indirectly) the harvest cycles for different crop types with an enhancement from using a seasonal NDVI time series (Zhu and Liu, 2014). Figure 4 shows harvest and regeneration for an agriculture point, while the forest plantation point grows over time and levels off in the dryer season (summer) when the trees may not be at peak vigor. In this figure the NDVI values for the two planted types do not converge. This specific case was corroborated via preliminary analyses using Sentinel-2 MSI.

Across years and time natural forests have, in general, higher NDVIs than forest plantations (Figure 5). NDVI variability is also greater in forest plantations for all dates except March 2018. The wide variability of plantation NDVIs is likely due to the different types and ages of stands within the plantation class (see the top row of Figure 9 for an example of the change in appearance of plantations from establishment to maturity). However, even given this variability, it is clear from Figure 5 that the plantation and natural forest classes are generally separable using NDVI alone.

At the study design phase, we tested imagery from the Landsat 8 Operational Land Imager (30 m) and from the 20-m Sentinel-2 MSI bands (SWIR and red edge). However (see, e.g., Figure 3), neither of these sensors had sufficient resolution to detect smallholder forest plantations as trees outside forests. Even the inclusion of the SWIR bands (both sensors) and red-edge bands (Sentinel-2 MSI) could not compensate for the decreased spatial resolution. Keep in mind, however, that this preliminary analysis was focused on just the identification of forest plantations without attempting greater categorical specificity (such as species or other taxonomic groupings). Discrimination of tree species in the tropics has been shown to improve using the SWIR (Ferreira *et al*., 2015).

Forest expansion occurs from two main causes: forest plantation establishment or the spontaneous reforestation of abandoned land (Mather, 2007). For LCLUC science, defining what type of forest is expanding will be vital for ecological and economic modeling. As such, our study focused on three main land cover classes in a hierarchical sampling design: nonforest, natural forest, and forest plantation. This now vetted approach to forest plantation detection can be further utilized in subsequent efforts that map natural vs. planted forests.

High frequency of temporal coverage and high spatial resolution are both imperative for quantifying different forest types across a heterogeneous landscape, where natural forests and plantations are woven in and around each other (Roy *et al*., 2015). Sentinel-2 data proved sufficient to the task for block forest plantations in this instance. However, there are other realizations of trees outside forests, namely windbreaks, scattered trees, and linear plantations (Rawat *et al*., 2003) that will likely require higher resolution imagery for accurate quantification.

Conversion to agriculture, coupled with secondary dependencies on and scarcity of wood products, has driven the deforestation and degradation of natural forests in Southeast Asia (Paquette and Messier, 2010), thus mapping planted forests and natural forests separately will better document the distribution of natural versus anthropogenic systems. This unsupervised machine learning approach using remotely sensed data for land use and land cover mapping can be utilized as a baseline for forest analysis by providing a means for separation of the different uses that trees are subject to, that could be further utilized to increase levels of categorical specificity within the forest plantation class.

Finally, while we were successful in using supervised machine learning via the commonly utilized random forests algorithm, deep learning is also gaining popularity in remote sensing science. It has strong potential for mapping at this and, in particular, increased levels of categorical specificity (Ienco, 2017), which requires a substantial increase in training data.

6. Conclusions

Intra- and interannual VNIR reflectance data from Sentinel-2 MSI, coupled with high quality training data that capture spectro-temporal variability, enable fine-scale forest plantation detection in Andhra Pradesh using a common machine learning approach. The spatial resolution and radiometric quality of the Sentinel-2 data, coupled with their availability at no-cost, make them particularly suitable to mapping trees outside forests. Quantifying the ecosystem services provided by smallholder plantation forests in South and Southeast Asia will require regular, accurate mapping to capture both status and change. These future efforts, whether by state or non-state actors, will be engendered by building on the lessons learned from this case study in Andhra Pradesh.

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Tables

Table 1. In situ data on forest plantations provided by collaborators was supplemented with additional training data points and aggregated into 3 classes: nonforest, natural forest, and forest plantation.

Land Cover Class	Number of Points	Aggregate Class
Agriculture	555	
Aquaculture	153	
Ground (or barren)	81	Nonforest
Sand	110	*n = 1,467*
Urban	119	
Shrub/Scrub	224	
Water	225	
Natural Forest	241	Natural Forest
Mangrove	58	*n = 299*
Forest Plantation	253	Forest Plantation
Palm Plantation	211	*n = 464*

Table 2. Julia DecisionTree.jl random forest classifier parameter values and descriptions.

Parameter	Value	Description
num_folds	5	Number of cross validation iterations
num_subfeatures	-1	Number of features to select at random
num_trees	50	Number of individual decision trees
sampling_proportion	.7	Proportion of samples per tree
max_tree_depth	-1	Maximum depth of the decision tree, grown to maximum extent
min_leaf_samples	10	Minimum number of samples each leaf needs to have
min_samples_split	5	Minimum number of samples in needed for a split
purity_increase_min	0.0	Minimum purity needed for a split used for post-pruning

Table 3. Average error matrix from the 5-fold cross-validation, n = 446 samples/fold. Note the lowest values of confusion are present between natural forest and plantation, while the highest values are separation of the forest classes from nonforest, which is expected considering presence of trees along croplands and urban mosaics.

	Nonforest	Natural Forest	Forest Plantation
Nonforest	282.4	7.4	3.6
Natural Forest	3.4	54.6	1.8
Forest Plantation	7.2	.4	85.2

Table 4. Accuracy summary statistics calculated from average error matrix.

Land Cover Class	User's Accuracy	Producer's Accuracy	Overall Accuracy	Kappa
Nonforest	96	96.1		
Natural Forest	92	86.3	94.3	88.7
Forest Plantation	90.1	94		