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Integration of Sentinel optical and radar data for mapping smallholder coffee production systems in Vietnam

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Abstract

Perennial commodity crops, such as coffee, often play a large role globally in agricultural markets and supply chains and locally in livelihoods, poverty reduction, and biodiversity. Yet, the production of spatial information on these crops are often overlooked in favor of annual food crops. Remote sensing detection of coffee faces a particular set of challenges due to persistent cloud cover in the tropical “coffee belt,” hilly topography in coffee growing regions, diversity of coffee growing systems, and spectral similarity to other tree crops and agricultural land. Looking at the major coffee growing region in Dak Lak, Vietnam, we integrate multi-temporal 10m optical Sentinel-2 and Sentinel-1 SAR data in order to map three coffee production systems: i) open-canopy sun coffee, ii) intercropped and other shaded coffee and iii) newly planted or young coffee.

Leveraging Google Earth Engine (GEE), we compute five sets of features in order to best enhance separability *between* coffee and other land cover *and within* coffee production systems. The features include Sentinel-2 dry and wet season composites, Sentinel-1 texture features, Sentinel-1 spatiotemporal metrics, and topographic features. Using a random forest classification algorithm, we produce a 9-class land cover map including our three coffee production classes and a binary coffee / non-coffee map. The binary map has an overall accuracy of 89% and the three coffee production systems have user accuracies of 65, 56, 71% for sun coffee, intercropped coffee and newly planted coffee, respectively. This is a first effort at large-scale distinction of within-crop production styles and has implications across many applications. The binary coffee map can be used as a high-resolution crop mask, whereas the detailed land cover map can inform monitoring of deforestation dynamics, biodiversity, sustainability certification and implementation of climate adaptation strategies. This work offers a scalable approach to integrating optical and radar Sentinel data for production of spatially explicit agricultural information and contributes particularly to tree crop and agroforestry mapping, which often is overlooked in between agricultural and forestry sciences.

Key words: agroforestry, smallholder agriculture, crop mask, Sentinel-1, Sentinel-2, data fusion, Google Earth Engine, random forest

1. Introduction

Tree crops contribute to food and livelihood security, poverty alleviation, agricultural Gross Domestic Product (GDP) and export earnings of tropical countries, especially commodity crops such as coffee, cocoa and rubber (Dawson et al., 2014; Ha and Shively, 2007; Läderach et al., 2017; Leakey, 2017). Over 70 tropical countries contribute to global coffee production, now over 10 million tons annually (FAO, accessed: 01-11-2020). In Vietnam, the 2^{nd} largest coffee producer worldwide, production is dominated by smallholders owning less than 2 ha farmland (Fridell, 2014). There is an increasing demand for detailed information on the spatial dynamics of such commodity tree crops to better understand deforestation drivers, sustainability certification, livelihood preservation, and how a changing climate intersects with these aspects (Hunt et al., 2020; Pham et al., 2019). However, accurately mapping coffee production systems, especially distinguishing shade or intercropped system (e.g. multi-canopy) and young coffee, remains challenging. Our study contributes to this effort by building on applied remote sensing methods to derive cropped areas and planting styles in the coffee landscape in Dak Lak province, Vietnam. In this study, we focus on the robusta (*Coffea robusta*) growing region in Dak Lak, as there is a significantly less research on robusta compared to arabica (*Coffea arabica*), worldwide (Hunt et al., 2020; Kath et al., 2020; Pham et al., 2019).

Coffee in Vietnam is grown in a variety of agroecosystems. After many years of mostly sun-grown coffee production systems with regional implications for reduced habitat, biodiversity and water-resource related ecosystem services, Vietnam smallholders have recently shown interest in diversification and more sustainable production, due to various economic and climatic factors (Pham et al., 2020; Thi and Chaovanapoonphol, 2014). This diversification has resulted in mixed agroforestry systems, such as intercropped plots where e.g. peppercorn, fruit and nut trees are grown in between coffee trees, or nitrogen-fixing boundary trees are planted on plot borders. In Vietnam, the focus is on “intercropping” systems, similar to terms like shade, polyculture, multi-layer canopy. These production systems all entail that multiple tree species are planted alongside coffee. These coffee production systems all have their ecosystem service benefits in micro-climate temperature regulation, water retention (through reduced evapotranspiration), increase in biodiversity and even coffee quality (De Beenhouwer et al., 2013; de Carvalho et al., 2020; Jezeer et al., 2019; Nesper et al., 2017). We are therefore motivated to not only map coffee area but to also separate coffee sub-classes, including a distinction between sun and intercropped coffee as a means of investigating on-the-farm agroforestry implementation.

1.1. Current Literature

Accurately mapping smallholder coffee production systems, especially the intercropped coffee plots, has been challenging despite recent advances in remote sensing data and methods. This challenge is compounded in that coffee and particularly intercropped systems are often associated with complex and diverse management practices, which influences spectral signal in various ways (Hung Anh et al., 2019; Nogueira et al., 2018). There is limited work on distinguishing coffee production systems, i.e. coffee sub-categories (Hunt et al., 2020). Only a handful of studies have distinguished shade (closed-canopy or mixed) coffee from sun coffee (open-canopy or production) at mid-resolutions, such as Landsat (Cordero-Sancho and Sader, 2007; Kawakubo and Pérez Machado, 2016; Ortega-Huerta et al., 2012). Even fewer works distinguish coffee age classes (Chemura et al.,2017; Chemura and Mutanga, 2016). And a single work classifies multiple production systems: closed canopy, shade polyculture, sun monoculture and newly planted (sparse cover), using high resolution IKONOS imagery (Widayati et al., 2003).

There are many documented challenges to mapping in coffee landscapes using remotely sensed imagery, namely: (i) diversity in size and structure of coffee fields, (ii) steep slopes and their topographic effects, (iii) wet season cloud coverage in coffee-growing tropics, and (iv) similarity in the infrared spectral signal of coffee farms and adjacent mature plantations, young plantations and agricultural land (Cordero-Sancho and Sader, 2007; Gomez et al., 2010; Kelley et al., 2018; Mukashema et al., 2014; Nogueira et al., 2018; Ortega-Huerta et al., 2012). The fusion of optical and synthetic aperture radar (SAR, specifically Sentinel-1 and Sentinel-2 data) has been highlighted as particularly promising for coffee mapping (Hunt et al., 2020). Inclusion of Sentinel-1 has the main advantage that it is not restricted by cloud coverage, a common barrier during the tropical rainy season. There are a growing number of studies integrating these two data types in plantation mapping (Liu and Chen, 2019; Poortinga et al., 2019), annual crop mapping (Clerici et al., 2017; Denize et al., 2018; Jin et al., 2019; Mercier et al., 2019; Qadir and Mondal, 2020; Sun et al., 2019) and even detection of single trees outside of forests (Brandt and Stolle, 2021); however, the integration of Sentinel-1 and 2 data has not yet been applied to coffee production systems.

Along the same line of fusion of multiple satellite data, the integration of multiple remote sensing derived feature types (e.g. not only spectral, but including texture, weather indicators, topographic) has also been shown to be beneficial in heterogenous agricultural and coffee mapping (Gomez et al., 2010; Hunt et al., 2020; Kelley et al., 2018). Most commonly, topographic information is regularly included in many coffee mapping studies (Cordero t-Sancho and Sac al., 2014), which can be attributed to coffee's suitability at higher elevations (DaMatta et al., 2007). Precipitation or temperature features (Cordero -Sancho and Sader, 2007; Kelley et al., 2018) and texture features (Gaertner, 2017; Gomez et al., 2010; Tsai and Chen, 2017) are rapidly becoming key in difficult-to-map coffee regions. Studies that include texture features often use high-resolution proprietary data such as WorldView (Gaertner, 2017) or Quickbird (Gomez et al., 2010), or focus on mapping or distinguishing other tree crops such as cocoa, rubber, oil palm (Burnett et al., 2019; Gao et al., 2015; Nomura and Mitchard, 2018; Numbisi et al., 2019; Torbick et al., 2016). Notably, Gray Level Co-occurrence Matrices (GLCM) texture measures were derived from Sentinel-1 for cocoa mapping in Numbisi et al. (2019). Texture measures were demonstrated to have more use in SAR images compared to optical and are of added value in heterogenous landscapes (Mishra et al., 2019).

We integrate Sentinel-2 optical and Sentinel-1 SAR data and generate the first map of its kind for the different coffee production systems at the plot-level in Dak Lak, Vietnam. The coffee production systems, or coffee subcategories that we target are: i) newly planted coffee (< 3 years old), ii) intercropped coffee and iii) sun (open-canopy) coffee. We build on the work of employing multiple feature types in a heterogenous smallholder landscape by employing: optical spectral features, optical derived indices (such as vegetation indices), SAR spectral and spatiotemporal features, SAR texture features, and topographic features.

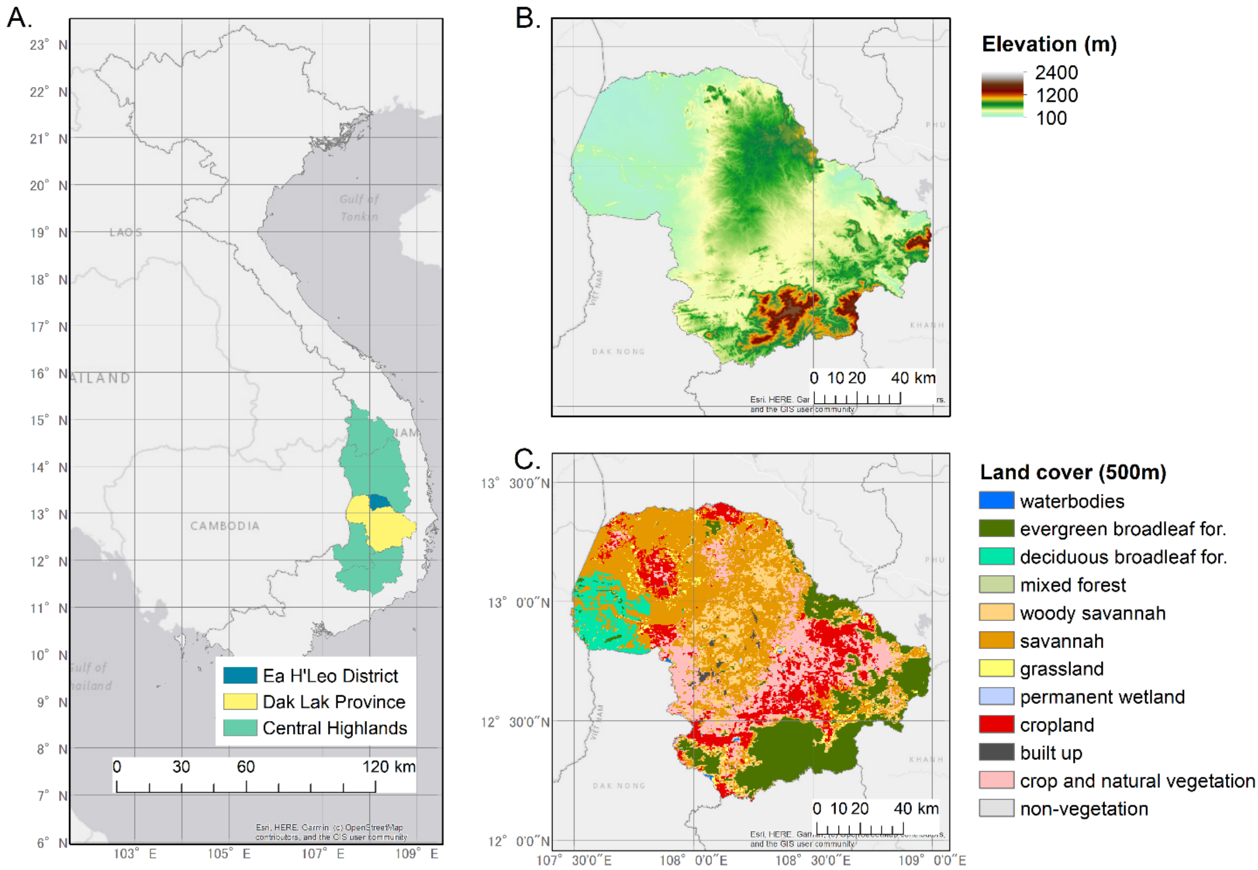

Figure 1. A) The Central Highlands region, Dak Lak province, and Ea H'Leo district; B) Elevation in Dak Lak (Farr et al., 2007) and C) Land cover map of Dak Lak, MODIS-derived land cover product (Friedl & Sulla-Menashe, 2015).

2. Study Area

The province of Dak Lak (with an area of ~13,000 km^2) is situated in the middle of the Central Highlands, a hilly region of Vietnam (Figure 1). The southern, high-elevation border is covered by tropical evergreen forest, and the northwestern, low-elevation corner by dry deciduous forest. A large portion of the province is dominated by agricultural land: perennials such as coffee, cashew, and rubber and annual crops such as rice and cassava. The Central Highlands has been defined as an "agricultural frontier region" (Agergaard et al., 2009; Grogan et al., 2015; Meyfroidt et al., 2013; Müller and Zeller, 2002; Phuc and Tran, 2014).These frontier dynamics are often connected to cash crops, perennial crops grown for the external market such as a coffee and rubber (Meyfroidt et al., 2013). In the 1990s there was a "coffee boom," where Vietnamese farmers planted over a million hectares (10,000 km^2) of coffee (De Ha and Shively, 2007). More recently there is an emerging trend of forest and annual cropland conversion for rubber plantations.

The coffee phenological cycle is many ways linked to seasonal weather patterns. The Central Highlands has a dry season (December - March) and a wet (rainy) season (April - November), with first rains in mid-April or early May and lasting into November (Pham - Thanh et al., 2020). The flowering period for coffee occurs during the dry season, where rainfall is low and evaporation is high. Because of this, farmers irrigate to start cherry formation, primarily in January and February (Amarasinghe et al., 2015; Byrareddy, 2020; Pham et al., 2020). The interactions between climate and management is a prominent process occurring in the coffee landscape in Dak Lak and the Central Highlands.

3. Data and Methods

We combine optical and radar satellite data to create i) a detailed land cover map of the coffee landscape (9 classes), targeting different coffee production classes and ii) a binary map of coffee/non-coffee in order to characterize the spatial distribution of where coffee is grown in Dak Lak. The model was developed on the basis of features and approaches from: (a) Jin et al., (2019), who use multiple S1 & S2 features for crop mapping in a smallholder landscape,(b) Poortinga et al., (2019), who integrate S1, S2, and Landsat-8 composites in a tree crop landscape, and (c) Kelley et al., (2019), who map coffee using multiple data, including optical seasonal composites, as well as through region-specific consideration in a calibration phase. The more detailed land cover map can be used as a base map to examine the evolution of different land uses/covers, whereas the binary map has applications as a more traditional “crop mask.” To do this, we implement a random forest classifier in Google Earth Engine (GEE) using optical, radar and topographic data as input features and training and test data collected via Collect Earth relying on high-resolution imagery.

In order to best target such a complex target as coffee, we build our feature set and approach based on the follow ecophysiological and plot characteristics of sun, intercropped and new coffee:

On separability of rubber and coffee:

There are ecophysiological characteristics that can help distinguish mature rubber and sun coffee. These are differences in foliage patterns, tree density and tree height. Coffee is an evergreen tree while rubber is deciduous, losing leaves annually in the dry season. Rubber trees are planted much closer together and almost quadruple the height of a mature coffee tree (standing up to 20m tall and ~5m tall, respectively). We hypothesize that seasonal optical imagery would capture the differences in foliage, particularly in the dry season, and that S1 C-band backscatter would capture the double scatter of the coffee canopy and the soil in a less dense sun coffee plot in order to distinguish these two dominant plantation crops.

Additionally, coffee and rubber have different growing patterns, i.e. coffee is almost exclusively planted in basaltic soils, often after clearing evergreen forests. Rubber, on the other hand, is found in low-lying land, less constrained by soil type, and often organized in expansive plots (very rarely in the same smallholder and ad-hoc patterns similar to coffee). This spatial pattern can help to distinguish mature rubber and sun coffee, but also cleared rubber from newly planted coffee. This hypothesis was demonstrated in part by the importance of elevation in both the calibration of our classification model at the district level in Ea H'Leo (Figure S1) and in our final land cover model at the province level of Dak Lak (Figure S1 & S2).

Further, we also consider the timing of planting coffee saplings (at the beginning of the wet season), for the distinction of newly planted coffee. There are two field-level characteristics we consider to distinguish it from rubber: i) there is a checkboard-like pattern from the holes dug for the coffee trees (particularly for sun coffee) and ii) newly planted coffee is often fertilized. We hypothesize that our GLCM texture variables could help to contextualize the surroundings of the newly planted coffee to better distinguish cleared rubber, newly planted coffee and other bare soil. We draw from nitrogen management monitoring literature to hypothesize that fertilization and soil properties associate with basaltic soils (reddish-brown) can be detected through the visible band remote sensing (Blaes et al., 2016).

On the separability of sun coffee and intercropped coffee:

The plot characteristics of sun and intercropped coffee differ in the following ways (non-exclusively) in which they would be distinguishable with the sensors and features used in our study: i) higher moisture (less evapotranspiration) in intercropped coffee, ii) thicker canopy and ground cover (rather than bare soil), and iii) "rougher" or more textured canopy for intercropped coffee (Assefa and Gobena, 2019; Padovan et al., 2018; Siebert, 2002). Sentinel-2 swir bands and Sentinel-1 bands are both sensitive to water and would entail that intercropping has a higher reflectance and backscatter, for S2 and S1, respectively (Figure S2 & S3). S1 GLCM texture features were designed primarily with distinguishing in-plot canopy texture between the two coffee production systems. This drove our choice of window sizes (further explained in Section 3.3).

3.1. Remote Sensing Data

In our multi-sensor approach, three remote sensing data types – optical data, SAR data and topographic information – were integrated as predictors for the coffee classification. We used 10m-60m optical Sentinel-2 (S2) Surface Reflectance (SR), 10m SAR C-band Sentinel-1 (S1) Ground Range Data (GRD), and topographic Shuttle Radar Topographic Mission (SRTM) 30m DEM data, accessed on GEE platform (Copernicus, retrieved: 11-12-2019; Farr et al., 2007; Gorelick et al., 2017). It was key to include 10m resolution optical and radar in this smallholder landscape as it allows for distinguishing cropping systems at the smallholder plot-level. Additionally, SAR data added a temporally consistent data source in the cloudy tropical and hilly region and the C-band wavelength at 5.6cm is more suitable than the L-band sensor, typically used to monitor forest, due to coffee's smaller crown size.

Sentinel-2 SR images were accessed for 01 November, 2018 through 31 October, 2019 covering both wet and dry seasons (Table S1, Table S2). A filter was applied to consider images with a cloudy pixel percent less than 10%, an estimated data attribute to all Sentinel scenes. This was particularly important as Sentinel cloud masks are not yet as developed as e.g. Landsat cloud masks. Using highly clouded scenes will likely result in cloud artefacts, impacting the spectral signal.

Sentinel-1 GRD data were obtained for the same date range. We utilize data from vertical transmit and vertical receive (VV) and vertical transmit and horizontal receive (VH) polarization (as this is what is available in this region) and interferometric wide swath acquisition mode (Table S1, Table S2). The Copernicus S1 GRD data is already multi-looked (converted from slant range) and projected to ground level. The data made available through GEE has been pre-processed in the Sentinel Application Platform (SNAP) to apply the orbit file, perform thermal noise removal, radiometric calibration and terrain correction, using SRTM30 (ESA- S1TBX Sentinel-1 Toolbox, accessed: 05-02-2021).

3.2. <u>Reference Data & Classification Scheme</u>

Reference data refers to all point data used to parameterize, train and test the classification. These points were collected using Collect Earth (Bey et al., 2016) and Google Earth high-resolution imagery from the year 2019 in two rounds: at the province level across Dak Lak, and at the sub-province district level in Ea H'Leo (see Figure 1). This data collection was facilitated by a field visit in summer 2019 where location points for different land cover classes were collected using a handheld smart device. For both sets of reference data (province and district level), we randomly sampled and labelled following the classification scheme in Figure 2. If randomly sampled points fell in between classes or in a mixed area, they were resampled within one km for all relevant classes. Additionally, iterative opportunistic sampling was used to sample particularly from the coffee target classes and cultivated vegetation (both annual and perennial crop) classes, the classes that are most often confused with coffee (Figure 2*)*. The Ea H'Leo set (600 points) was used to test and select a subset of features to use in the classifier at the full province level, in a calibration and feature reduction phase. The Dak Lak dataset (~1000 points) was randomly split 70/30 into a train and test dataset for the random forest classifier, ensuring that at least 50 points for each of our 9 classes were part of training dataset.

The reference data classification scheme was collected at the "lowest denominator," most detailed categorical level and aggregated as needed for each of the classifications (Table 1; Bey et al., 2020). This modular scheme allowed for flexibility in re-grouping classes based on the classification needs and application. For example, we use this dataset to classify a detailed land cover map, targeting coffee sub-classes, and in a binary coffee/ non-coffee map.

Table 1. Classification scheme, with example high-resolution imagery from Google Earth imagery for the reference data (points), and how it was aggregated for the detailed land cover map and binary classification scheme.

Reference scheme	***Detailed land cover scheme***	***Binary classification scheme***	***Reference image from Google Earth***
Sun coffee (coffee with an open canopy)	sun coffee	coffee	
Intercropped or other shade coffee	intercropped coffee	coffee	
Newly planted coffee (sparse)	newly planted coffee	coffee	
Other tree crop (including e.g. acacia, cashew)	partially vegetated	non-coffee	
Newly planted fruit or nut tree crop (sparse)	upland crop	non-coffee	
Upland crop	upland crop	non-coffee	

Shrubland	partially vegetated	non-coffee	
Low or no vegetation (including bare soil)	partially vegetated	non-coffee	
Mature rubber plantation	heavily vegetated or forested	non-coffee	
Clear or young rubber	upland crop	non-coffee	
Dry deciduous forest	partially vegetated	non-coffee	
Evergreen forest	heavily vegetated or forested	non-coffee	
Mixed forest	heavily vegetated or forested	non-coffee	

Wet crop (rice)	rice	non-coffee	
Built	built	non-coffee	
Water	water	non-coffee	

For the detailed land cover map, we aggregated non-target (non-coffee) classes that were most often confused in the calibration phase. This includes the aggregation of dry deciduous, other tree crop, and low vegetation, where our classifier is most likely confusing the low foliage deciduous forest with low or no vegetation particularly in the dry season. For the binary coffee map, the detailed land cover labels were reclassified as coffee or non-coffee.

3.3. <u>Data Pre-processing</u>

Each scene in the Sentinel-2 Surface Reflectance series were cloud masked using the GEE implemented cloudscore algorithm and shadow masked using temporal dark outlier mask (TDOM) (Housman et al., 2018; Schmitt et al., 2019). For each cloud and shadow masked S2 scene, a stack of spectral indices was calculated and appended, creating a collection of 66 scenes with the 10 reflectance bands and 13 computed indices (Table S3). This collection was then split into dry season from 01 November, 2018 to 15 April, 2019 and wet season, from 01 May to 31 October, 2019. The median values from the 44 dry season scenes and 22 wet season scenes were taken to create two seasonal image stacks from the S2 data (Figure

2). Although there are many ways to composite an image, we decided for the median due to limited scenes in the wet season, where max or min values could be contaminated by cloud and cloud shadow.

Our image search for the study area returned 90 ascending VV, 90 ascending VH, 60 descending VV, and 60 ascending VH scenes (Table S4). An initial variable importance analysis (random forest) with the Ea H'Leo district reference set showed a consistently higher importance for descending scenes, perhaps due to topography or the different pass times of ascending and descending. A preliminary look at VV and VH backscatter also showed a more defined signal between sun and intercropped coffee for VH (Figure S3). Therefore, SAR-derived temporal statistics and texture features at the Dak Lak level were only calculated for the descending scenes for both polarizations (VV & VH). First, spectral temporal statistics were calculated for the VV descending and VH descending time series. These metrics, including median, 25th and 75th percentile and standard deviation across the time series of scenes, are often used for optical Landsat imagery in less cloudy regions, such as in Hu et al., (2018); Müller et al., (2015); Pflugmacher et al., (2019). Yet such metrics are not as effective in sparse time series, as is often the case for wet season optical data in the tropics. S1 radar data, with its cloud non-dependence and dense time series (revisits roughly ~6 days) allows us to leverage the added value information that temporal statistics can offer.

In addition to the S1 spectral temporal metrics, 8 Gray Level Co-occurrence Matrix (GLCM) texture variables (Haralick et al., 1973) were calculated for the median composite of the descending VH series using a 5x5 moving window, with a displacement of 1, and averaged over four spatial orientations (Figure 2). After testing moving windows of size 3, 5, and 7 in Ea H'Leo, a 5x5 pixel moving window was chosen to best capture the plot-level texture, particularly between sun and intercropped coffee. S1 SAR textural information has been shown to be particularly beneficial in heterogenous landscape (Mishra et al., 2019), distinguishing between smallholder and large-scale plantations (Oon et al., 2019), but has also been applied for agroforestry mapping, as is done for a cocoa landscape in Numbisi et al., (2019).

The S2, S1 and topography image stacks were all prepared and combined into a single stack in GEE. Although the random forest classifier has been assumed to deal well with high-dimensional data, it has been shown that large numbers of correlated input features can disadvantage the minority class (Waldner et al., 2019), especially when trying to capture small proportion target classes (such as newly planted coffee). In order to reduce the 67 prepared features and multicollinearity, we applied a variance inflation factor (VIF). The full feature stack was exported into R and a VIF: $\frac{1}{1-R^2}$, where R^2 is the coefficient of determination, was computed for each of the 67 features, by sampling at the Ea H'leo reference points. Any feature with a VIF higher than 10 was removed, which is often considered the rule of thumb (O'Brien, 2007). This step resulted in 22 features, representing all five types: S2 wet and dry season composites, S1 spectral temporal metrics, S1 texture variables, and SRTM topographic variables (Table 2). These features were the input for the random forest classifier.

3.4. Calibration

Before running our final classifications, we calibrated our model at the sub-province level (Ea H'leo). Calibration entailed using the Ea H'leo reference data and our full feature set (67 features) as input into an initial classifier, inspecting confusion between classes, and variable importance metrics. The calibration phases tested multiple land cover classification schemes and informed the aggregation of classes that would best allow for the targeting of coffee. For example, natural forest and mature rubber plantations had high confusion most likely due to their high planting density and similarity in height. Additionally, in the north of Dak Lak, dry deciduous forest, low or no vegetation and "other tree crops," which in this area is primarily acacia, were being confused, most likely due to their similarities in low foliage during the dry season.

The variable importance analysis for Ea H'Leo aligned with the variable importance for Dak Lak. For example, ndti (normalized tillage index, a swir1 and swir2 normalization) and elevation maintained their relative importance in both Ea H'Leo and Dak Lak, across multiple runs. Lastly, in the calibration phase, we also reduced our feature set, using VIF (detailed in 3.3 Data pre-processing). This reduce collinearity between features (and minimizes OOBe), allowing for a more stable re-application of our method at a higher scale and in other areas.

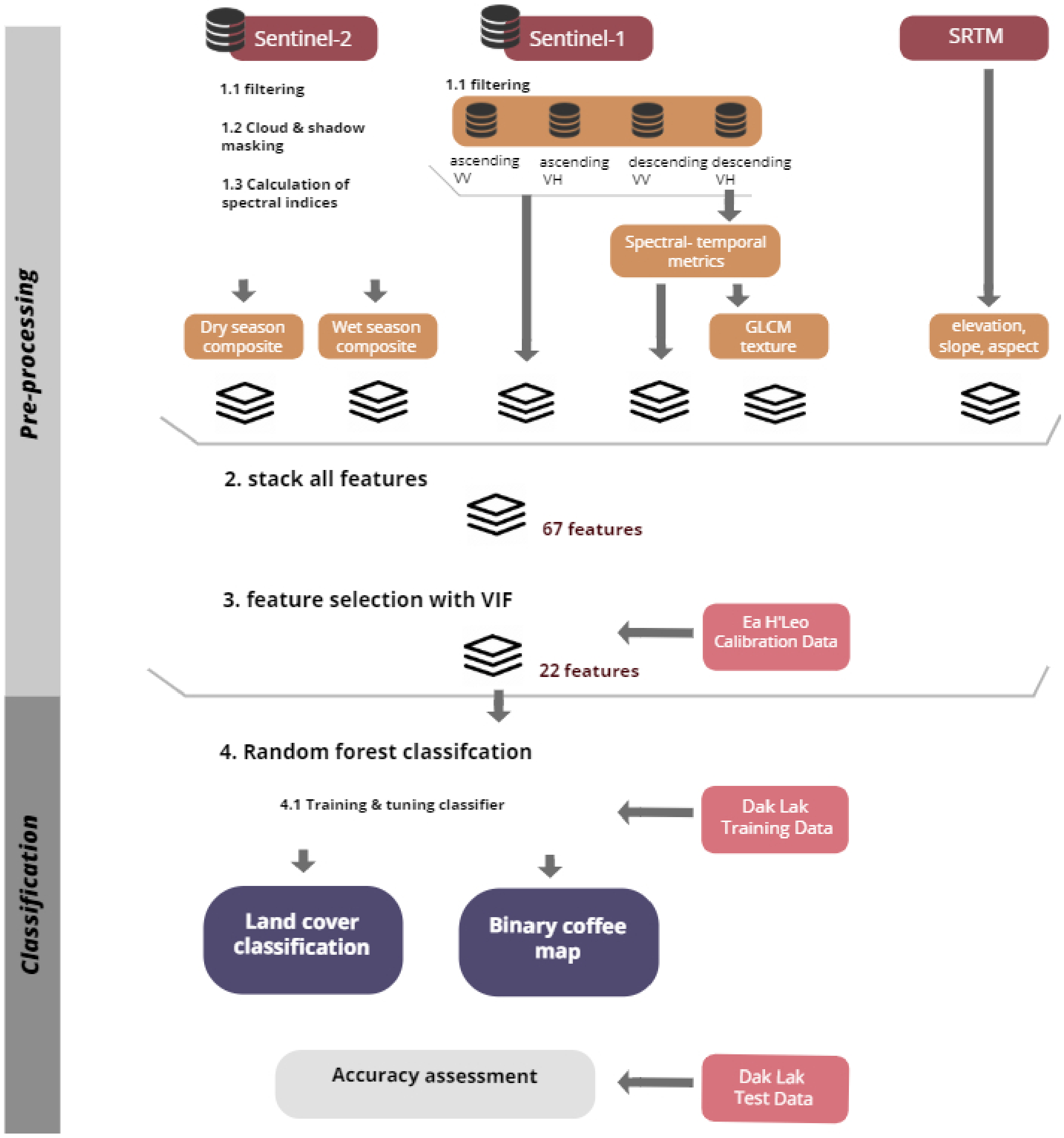

Figure 2. Methods workflow showing data used, pre-processing steps and classification inputs and outputs.

Table 2. Features inputted into the classifier after a feature reduction (using a Variable Inflation Factor method). The features are grouped in the 5 categories: Sentinel-2 derived features in the dry season; Sentinel-2 derived features in the wet season, Sentinel-1 spatiotemporal metrics (temporal statistics), Sentinel-1 texture metrics, and DEM-derived.

Category	***Features included (22)***
S2- dry season	blue nir Green Chlorophyll Vegetation Index (GCVI) Modified Crop Residue Cover (MCRC) Normalized Difference Tillage Index (NDTI)
S2- wet season	blue nir swir2 MTCI GCVI MCRC
S1 SAR (including spatiotemporal metrics)	VV asc median ratio VV:VH desc standard dev. VV desc 75^{th} percentile VV desc 75^{th} percentile VH desc
S1 SAR- texture metrics	GLCM correlation GLCM sum variance GLCM angular second moment (ASM)
DEM-derived metrics	elevation slope aspect

3.5. Classification

In order to create i) a detailed land cover map with coffee production systems specified and ii) a binary coffee mask, both at 10m resolution, two random forest classifiers were implemented in Google Earth Engine. Random forest (RF) is a machine learning algorithm hat uses a decision tree-based ensemble and bootstrap aggregation (bagging) of training data, described in the landmark paper (Breiman, 2001). RF is often used for remote sensing classification problems for its robustness compared to individual models, relative resistance to noise, ability to hand high-dimensionality, and ease of parameterization (Belgiu and Drăguţ, 2016; Hengl et al., 2018). There are three main user-defined hyperparameters for RF models: number of trees, number of variables per split and maximum number of splits. Number of trees is the number of individual models in the ensemble, or number of decision trees in the "forest." Number of variables per split (or node on a decision tree) is a restriction from 1 to the total number of features, that can be used to create the most separation at any specific node. If the number of variables per split is less, this creates more variation between the trees. And lastly, the maximum number of splits restricts the depth of the individual trees. Theoretically, the hyperparameter values shouldn't strongly influence the outputs, however practically, they need to be tuned (Scornet, 2017). The hyperparameters, number of trees and variables per split, were tuned using the out-of-bag error (OOBe) and step-wise test runs of all reasonable combinations (Table S5, Table S6). In GEE, we set bagging to 65% for the calculation of the internal OOBe used to tune the random forest model. Based on the tuning, we ran both the detailed land cover and binary classifiers with 2000 trees and 2 variables per split. We used the default for maximum depth of trees, unrestricted.

A random sub-selection of 70% of the Dak Lak reference data (Section 3.2) was used to train the random forest classifier, each training point could be thought of as a vector with associated values sampled from the 22 features, selected using VIF (Section 3.3). The detailed land cover map being trained on a 9-class schematic specified in the second column of Table 1 and the coffee mask being trained on with a binary coffee / non-coffee scheme.

In addition to the traditional accuracy assessment matrix, we would refer to another metric: quantity disagreement and allocation disagreement, as proposed by Pontius and Millones (2011) in substitution of kappa. Pontius and Millones argue that overall accuracy (agreement) and kappa provide only a positive evaluation and do not give information on the certainty of how a classification *does not* perform. Quantity disagreement can be defined as the differences between the reference data and the classification attributing to an imperfect match in the proportion of the categories. Allocation disagreement is defined as the differences in geographic spread of pixels between reference and classification. The "total disagreement," or the percentage of mismatch, between the reference and classification is the sum of the quantity and allocation disagreement.

For the detailed land cover classification, we also carried out sensitivity analysis by running our classifier with our feature subsets (S1 spectral temporal metrics, S1 GLCM texture features, S2 wet season, S2 dry season, topographic) and various combinations of these subsets.

4. Results

4.1. Detailed Land Cover Map

The detailed land cover classification offers a method for employing open 10m Sentinel optical and radar data to characterize plot-level production system for coffee within a highly heterogeneous landscape, while also covering a province-level area of 13,000 km^2.

Our classified land cover map shows coffee plantations clustered in the middle stripe of Dak Lak, in mid-range elevation (Figure 3, Figure 4D). Visually, intercropping and other shade systems are concentrated around Buon Ma Thuot, the Central Highland's "coffee capital" (Figure 4E). New coffee plantations are often on increasing elevations, with concentrations in the Northeast in Ea H'Leo (Figure 4A) and a patch of new coffee landscape in M'Drak (Figure 4B). The overall accuracy is 72.5% (Table 4), with user accuracies of 64.5%, 56.0%, and 70.8% for sun, intercropped and newly planted coffee respectively. The classifier's most common confusion is between sun and intercropped coffee, as expected. We also find a slight over-classification of all coffee classes (and agricultural land) at the expense of the partially vegetated class.

Figure 4 also highlights how our classification captures patterns of high heterogeneity within the landscape. It is common that neighboring plots of sun, intercropped and newly planted coffee are often patchworked, along with other annual and perennial crops or because farmers plant coffee gardens next to their houses. Our classifier was able to represent these intricacies of the landscape with good agreement of this challenging task. Our classification and reference data had a quantity difference of 6.2% and an allocation difference of 21.3%, with the majority of the disagreement or error attributed to spatial mismatch, primarily in the partially vegetated class (Table 5).

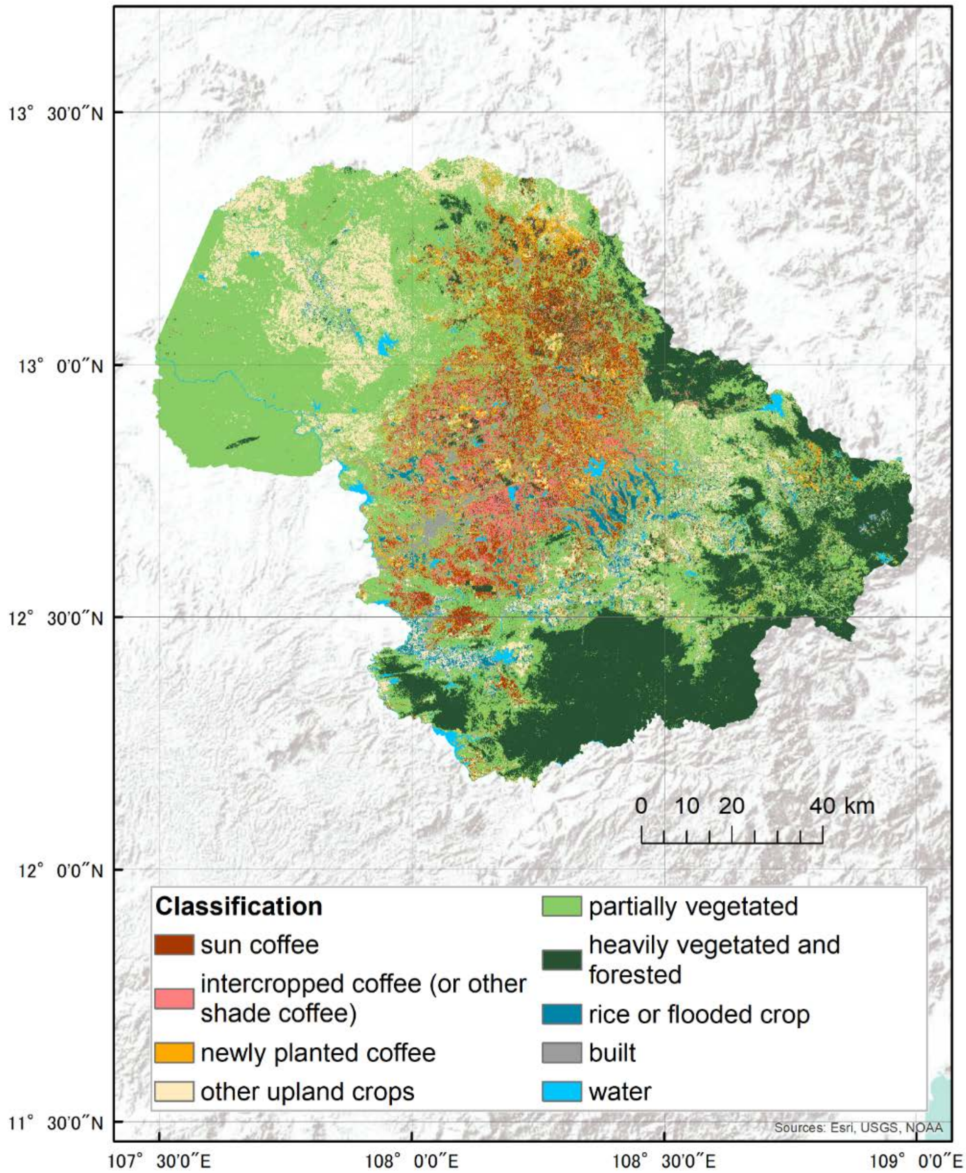

Figure 3. Map of detailed land cover classification for Dak Lak at 10-m resolution.

Table 4. Accuracy assessment for detailed land cover classification.

detailed land cover classification

test data

	sun	intercropped	newly planted	upland crop	partially vegetated	heavily vegetated	rice	built	water		count	user accuracy
sun	20	8	0	1	2	0	0	0	0		31	0.645
inter-cropped	8	14	0	0	2	0	0	1	0		25	0.560
newly planted	2	0	17	3	1	0	1	0	0		24	0.708
upland crop	1	0	4	25	4	0	3	0	0		37	0.676
partially vegetated	4	3	3	10	74	8	2	1	2		107	0.692
heavily vegetated	1	2	0	0	4	33	0	0	0		40	0.825
rice	0	0	2	4	0	1	15	0	0		22	0.682
built	0	0	0	0	0	0	0	18	0		18	1.000
water	0	0	0	0	0	0	1	0	19		20	0.950
count	36	27	26	43	87	42	22	20	21		**overall accuracy**	0.725
producer accuracy	0.556	0.519	0.654	0.581	0.851	0.786	0.682	0.900	0.905		**kappa**	0.675

Table 5. Overall disagreement metrics from Pontius and Millones (2011) for the detailed land cover map and the binary map. Agreement (or persistence) is equivalent to overall accuracy and total disagreement is the inverse.

	Agreement or Persistence	Commission or Loss	Omission or Gain	Total Disagreement	Quantity Disagreement	Allocation Disagreement
detailed land cover map	0.725	0.275	0.275	0.275	0.062	0.213
binary map	0.886	0.114	0.114	0.114	0.071	0.043

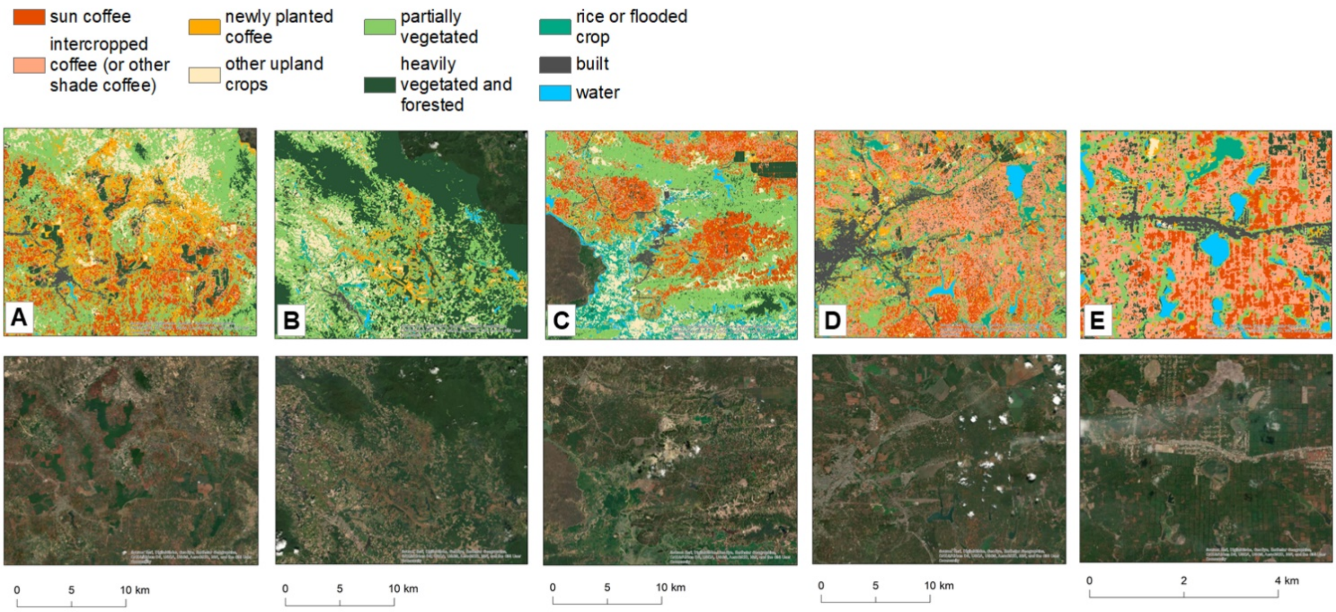

Figure 4. Closer look at the detailed land cover map in order to highlight specific landscape processes being captured, along with the corresponding satellite images: A) concentration of many new coffee plots, in a sun coffee and rubber landscape in Ea H'Leo, B) establishment of newly planted coffee in M'Drak (Eastern-most district), C) area dominated by sun coffee in Krong Ana, D) high concentration of intercropped or shade coffee near Buon Ma Thuot, E) zoomed in view near Buon Ma Thuot, an area of mixed sun and intercropped plots.

Table 6. The performance of detailed land cover model with inputs of feature subsets and combination of subsets. The 5 subsets are Sentinel-2 (S2) dry season composite, S2 wet season composite, Sentinel-1 (S1) spatiotemporal metrics, S1 Gray Level Occurrence Matric (GLCM) texture features and topographic features (SRTM). Overall accuracy (OA) and out-of-bag error (OOBe) are presented.

	Number of features	**OA**	**OOBe**
S2 dry only	22	0.65	0.40
S2 dry + wet	44	0.70	0.34
S2 all + SRTM	47	0.73	0.33
S1 spectral temporal	12	0.40	0.54
S1 GLCM	8	0.32	0.67
S1 all	20	0.46	0.52
S2 all + SRTM + S1 spectral temporal	59	0.74	0.30
S2 all + SRTM + S1 GLCM	55	0.73	0.32
all bands (full set)	67	0.67	0.31
reduced set (presented in Figure 4, Table 4)	22	0.73	0.28

Similar to other LULC mapping studies, optical seasonal composite gives an added information to the classifier, increasing both the overall accuracy and decreasing the OOBe (Table 6; Jin et al., 2019; Nguyen et al., 2019; Poortinga et al., 2019; Spracklen and Spracklen, 2021). While neither S1 subset performs well on its own, in combination with S2, the accuracy increases. The OOBe is higher in the model runs including GLCM texture, which may be due to the fact that some GLCM features are highly correlated (Haralick et al., 1973). Nevertheless, the inclusion of GLCM with optical and topographical information still increases accuracy and decreases OOBe.

4.2. Binary Coffee / Non-coffee Map

The binary coffee classification has an overall accuracy of 88.6% and a user accuracy for the coffee class of 89.4% (Table 7). The binary map was targeted with applications as a crop mask, since it is relatively uncommon to find one for tree crop at such a high spatial resolution with some degree of certainty (Inglada et al., 2015). This is highlighted in Figure 5, which shows a comparison of our coffee map (A) and other coffee maps (B-D) with coverage of Dak Lak.

Figure 5 helps to visualize the trade-off between spatial resolution, coverage, and information depth. For example, the Japanese Aerospace Exploration Agency (JAXA) land cover dataset (Figure 5B), offers a 10m spatial resolution for all of Vietnam but focuses on a rather general land cover scheme, without a specific coffee class. In the JAXA dataset, coffee crop is aggregated with other tree crops into the class “orchards.” A MODIS-derived dataset of “boom crops” (e.g. primarily rubber and other tree crops) in Mainland Southeast Asia, offers information on coffee at 250m resolution (Figure 5C). Our binary classification shows visual agreement with Figure 5C in terms of spatial distribution. Figure 5D shows a global gridded dataset on production area for FAO crops, where national and other administrative statistics are aggregated and re-distributed to the grid-cell level (Monfreda et al., 2008). In order to create the map shown in Figure 5D, cells with less than 1% of area covered by coffee were filtered out. It is noteworthy that no grid cell in Dak Lak had more than 3% area covered by coffee, according to the Monfreda dataset. The difference in spatial distribution between Figure 5A and 5D highlights the difficulties in scaling information on landscape dynamics to the global level.

With a producer accuracy for coffee of 66.3% in our detailed land cover map, the difference between the user and producer accuracy implies an over-assigning of pixels to coffee. The reference data was roughly proportional to land cover proportion for the binary map, as we changed the classification scheme without reducing the number of points (from a random sampling). As such, there were many more non-coffee training points compared to coffee training points and the over-assigning was unexpected. This is perhaps represented in the quantity and allocation disagreement, as quantity disagreement is higher than the allocation disagreement, at 7.1% and 4.3% respectively (Table 5).

Table 7. Accuracy assessment for binary classification.

	non-coffee	coffee		count	user accuracy
non-coffee	228	30		258	0.884
coffee	7	59		66	0.894
count	235	89		**overall accuracy**	0.886
producer accuracy	0.970	0.663		**kappa**	0.689

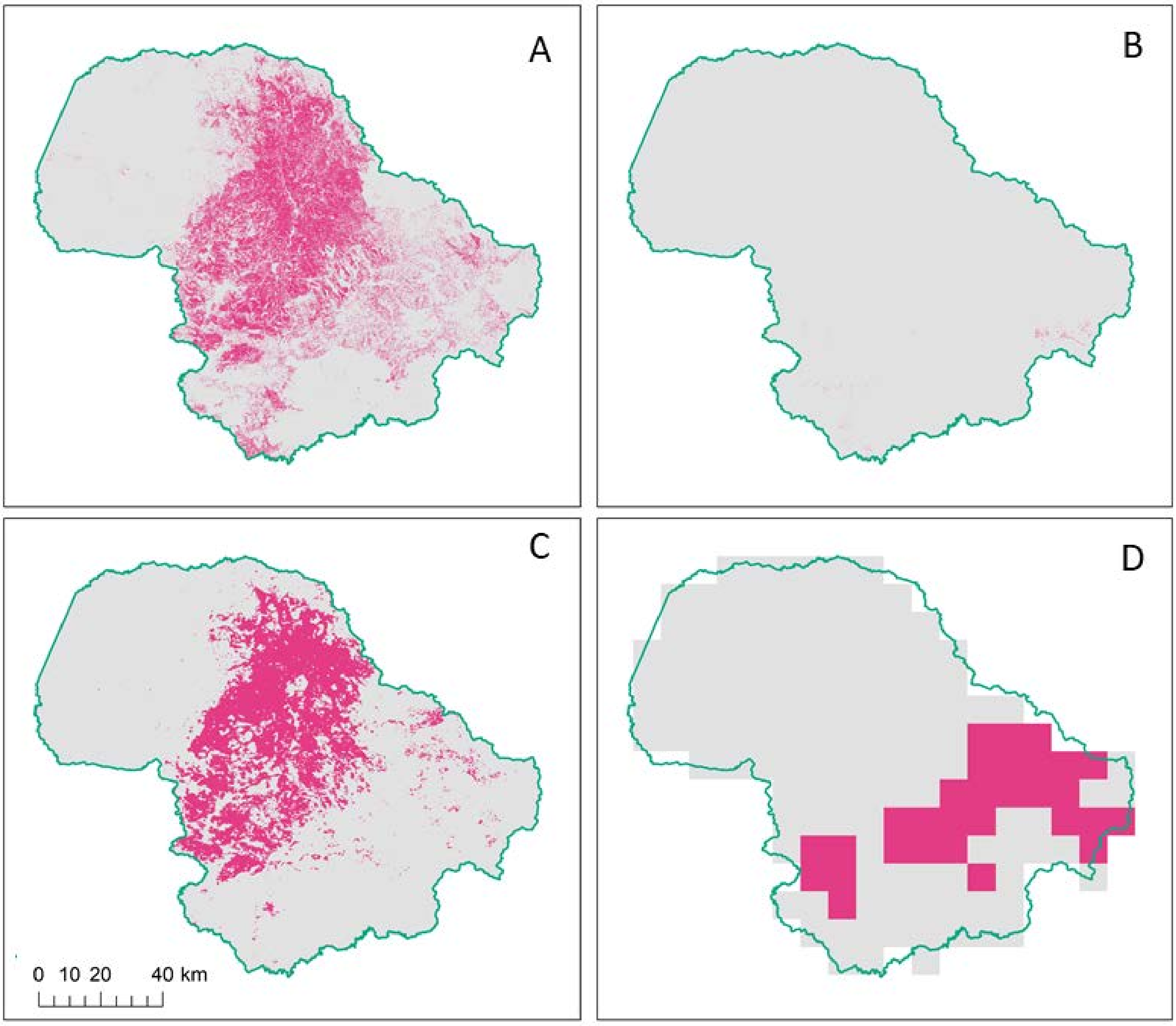

Figure 5. Comparison of A) the binary coffee map from this study; B) the orchard class from the 2017 JAXA Land cover map (10m), derived from S2, Landsat 7 & 8, ALOS/AVNIR-2, PALSAR, and SRTM (Duong et. al., 2018); C) Hurni and Fox's (2018) coffee class from their 2014 boom crop mapping in Mainland Southeast Asia (250m), MODIS-derived; D) Monfreda et al., (2008) “fraction of harvested area,” with a threshold of more than 1% coffee area harvested, disaggregated at the 5’ (~10km) grid cell from agricultural statistics for 2000.

5. Discussion

The method presented here builds on large-scale, crop-specific mapping using the open Sentinel asset, advancing geospatial methodology on mapping coffee as a complex target and generating plot-level thematic information within a heterogenous landscape. Most other large-scale Sentinel-based crop type mapping (Defou, 2019; Griffiths et al., 2019; Jin et al., 2019) targets annual crops, such as maize or wheat. We delve into the large-scale mapping of a tree crop, more along the lines of Poortinga et al. (2019), who mapped oil palm and rubber in a cross-border protected area between Myanmar & Thailand. To our knowledge, the work we present here is a first attempt at mapping coffee at the fine spatial resolution and large geographic scales using Sentinel data.

The integration of both Sentinel-2 and Sentinel-1 in crop type mapping is still being developed. The default is to rely solely on optical sensors; most work piloting the combination of optical and SAR Sentinel data for crop type mapping is carried out on a smaller geographic footprint (Denize et al., 2018; Sun et al., 2019). Nevertheless, recent studies have started to focus on crop-specific mapping combining these two data streams at regional to national scales (Jin et al., 2019; Poortinga et al., 2019). We contribute to this line of research for mapping coffee production systems. As demonstrated in Jin et al., (2019) and Poortinga et al., (2019), Sentinel-1 data has the added advantage of non-reliance on cloud-free days, allowing for a temporally constant information source to supplement optical data, especially in the cloudy tropics and sub-tropics. For coffee mapping or other lower biomass or sparse tree crops, C-band data (e.g. Sentinel-1 SAR), with its smaller wavelength of 3 – 5cm, is better suited compared to higher wavelength L-band data, often used for forest mapping.

As emphasized by Hunt et al. (2020), it is not common that coffee maps offer characterization or sub-plot information on the production system or age of coffee stand. We build off of the work using remote sensing to spatially characterize coffee production systems (Cordero -Huerta et Sanchez and Sader, 200 al., 2012; Widayati et al., 2003) and coffee age classes (Chemura et al., 2017; Chemura and Mutanga, 2016) by developing a method that allows implementation at larger geographic scale. This was enabled by i) open and easily accessible 10m Sentinel data, ii) GEE's cloud computing infrastructure, and iii) inclusion of a diverse set of features: seasonal information derived from optical imagery, radar temporal metrics, radar texture information and topographic information. The first two points speak to openly available research resources and infrastructure and the last speaks to a diversity of input features for representation of a diverse landscape. We conclude that each set of features brings something specific to the classifier’s ability to separate classes. This is supported by a feature importance not dominated by a specific feature, with all 22 features used in the classifier contributing to the overall accuracy (*Figure S4*). For example, we theorize that the use of texture metrics was particularly helpful in distinguishing between “textured” intercropping or other shade systems and homogeneous sun plantations that occur adjacent to each other. And according to a feature importance, the wet season SWIR2 band and the Normalized Difference Tillage Index, a ratio index between SWIR1 and SWIR2, had the highest contribution to accuracy (although not by a wide margin). This could be indicative of the importance of water regimes, such as irrigation schedule, or soil signals, such as background soil from less densely planted coffee, as SAR and SWIR are sensitive to water and soil signals.

In other smallholder landscapes it has been shown that that moderate resolution sensors, such as Landsat (30m), offer an advantage over MODIS (250m) in identifying cropping patterns in a Central Indian smallholder landscape (Jain et al., 2013), whereas very high-resolution Planet data (of 3 – 5cm) allows for sub-plot crop monitoring at a farm in Southern Brazil (Breunig et al., 2020). Our results fit in between these two works, presenting information on the plot-level production system with a 10m resolution at a landscape scale. This introduces a specific advantage over the previous work that cover Dak Lak (Figure 5). Only one other work with coverage of Dak Lak produced a map explicitly including coffee and did so using MODIS’s 250m resolution as part of a mapping effort targeting rubber in South East Asia (Hurni and Fox, 2018; *Figure 5c*). While JAXA produced a multi-sensor 10m land cover map for Vietnam, coffee was not a separate class, and was aggregated into “orchard,” defined as the intentional planting of trees or shrubs, which as a class did not perform well in Dak Lak (Duong et al., 2018).

This first mapping of “full coverage” coffee production styles, intercropped and newly planted coffee respectively, is useful in many applications. Information on where coffee is being re-planted or planted for the first time, represented by our class “newly planted coffee,” can aid in agricultural planning and monitoring deforestation (although both entail knowledge of the past land cover, e.g. through time series analysis, which will be mentioned later in the Discussion). Even though newly planted coffee is also confused with other agricultural land (primarily cleared rubber) and our classifier slightly over-estimates newly planted coffee, it is still a best-effort at addressing the two above-mentioned processes in the region. As a large percentage of coffee trees in the region are aging, 33% are 15-20 years and 31% are over 20 years, local governments are targeting replantation programs, such as Decision No. 2729/QD-UBND from the People’s Committee of Dak Lak (Hung Anh et al., 2019). The map and method presented here could offer one way of tracking progress, particularly in remote areas. Additionally, newly planted coffee in regions that are otherwise primarily natural vegetation or forest can give an indication for forest conversion, complementing prior work on forest frontiers and agricultural dynamics in the Central Highlands (Bourgoin et al., 2020; Meyfroidt et al., 2013; Phuc and Tran, 2014).

The spatial overview of implementation of agroforestry practices, represented by our class “intercropping,” can i) assist in monitoring of sustainability certification and ii) complement climate adaptation monitoring: two fields where monitoring is overwhelmingly undertaken through household surveys. It is also the novelty of our classification that we attempt to create spatially continuous dataset of information that is often collected and available at a point or clustered level. There are limitations in the producer accuracies of sun and intercropped coffee, primarily due to confusion between the two (as opposed to confusion with other classes). Nevertheless, a remote sensing effort at tracking coffee production systems is especially pertinent in hilly coffee regions, where field mapping is tricky due to remoteness and steep terrain of coffee growing areas and remote sensing can offer an information base layer for tracking sustainability and climate adaptation implementation. For example, we hypothesize that the visual hot spot of intercropping close to Buon Ma Thuot (Figure 4D &4E) could be attributed to the cluster of coffee companies, universities and research institutes on coffee that are supporting implementation of sustainable practice in coffee production including not only intercropping, but management of inputs, access to credit among other factors.

We present a method based on the landscape and agroecological characteristics in Dak Lak, however our approach was designed to scale from the district level, with calibration in Ea H'Leo, to the province level, in Dak Lak. Particularly, feature reduction through VIF was implemented to reduce overfitting, potentially allowing a better re-application or extrapolation of our method in similar areas. With similar agroecological characteristics through the Vietnamese Central Highlands, we imagine our feature set would perform well in neighboring coffee growing landscapes. In order to generalize our approach to other coffee growing regions, the optical seasonal composites would need to be adapted for other climates, and may depend on the number of seasons per year as well as onset, cessation and precipitation distribution. Using a similar approach, Kelley et al. (2018) maps coffee in a region of Nicaragua which has three seasons and the primary coffee production system is shade or traditional coffee. We hypothesize that our approach can be transferred to another climate conditions and coffee production systems, by changing the region-specific features, but the general transferability is not yet tested.

Tree crops are often completely excluded or have a high uncertainty in remote sensing based mapping (Fritz et al., 2011; Inglada et al., 2015; See et al., 2015). While our model targets coffee, we drew from mapping literature on similar tree crops: shade cocoa, coconut, rubber, and oil palm. While separating tree crop from surrounding land cover such as forest and other agriculture land, we would emphasize, in continuation of previous work, the added value of texture features in distinguishing landscape and cropping systems (Burnett et al., 2019; Gao et al., 2015; Gomez et al., 2010; Liu and Chen, 2019; Numbisi et al., 2019). We would also make the distinction between tree crops with a regular clearing rotation (such as rubber) and fruit and nut trees (such as a coffee and cocoa), and between monoculture dominated landscape, agroforestry dominated landscapes, and mixed monoculture and agroforestry. Aspects of our feature selection and processing, particularly the combination of multiple sensor and feature permutations, could be adapted specifically for fruit and nut tree, in mixed smallholder landscapes (Table 6). The adoption would need to be context specific in terms of seasonal characteristics and confounding land cover and crops.

The dataset we developed can serve as a baseline for a future time-series study. This could entail change detection for non-coffee (such as forest) to coffee, sun coffee to intercropped coffee, or the identification of replantation or abandonment of coffee. All of these land cover pathways can add a temporal dimension to the applications of deforestation and sustainability in coffee production. These land cover pathways would be extremely useful in building a timeline of a spatial continuous proxy for, e.g. forest vulnerability as done in Meyfroidt et al., (2013), or sustainable growing or climate adaptation proxies, an emerging interdisciplinary field between spatial sciences and sustainability science.

6. Conclusion

The work here offers a scalable method for mapping coffee production systems, and more broadly plantation and agroforestry systems, as well as presents a coffee map for a major world coffee-growing region, Dak Lak, Vietnam. In addition to benefiting from open 10m Sentinel-2 optical data and Sentinel-1 radar data, our method demonstrates the added value of heterogenous input features for a heterogenous landscape. Notably, cloud-independent Sentinel-1 SAR time series and texture features complement the established seasonal optical composites and SRTM topographic variables. The results present a binary coffee mask, with an overall accuracy of 89.4%, and a 9-class land cover map in a first effort to distinguish sun coffee, intercropped coffee and newly planted coffee, to broaden the applications of remote sensing in deriving thematic agricultural information at finer spatial scale.

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Links to GEE script:

Pre-processing: https://code.earthengine.google.com/268aad86925d374806d942635317d42c

Classification*:* https://code.earthengine.google.com/ee13aca08dd96f0ab0fe87f6c14dbdad

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List of Figure Captions

Figure 1. A) The Central Highlands region, Dak Lak province, and Ea H'Leo district; B) Elevation in Dak Lak (Farr et al., 2007) and C) Land cover map of Dak Lak, MODIS-dervied Land cover product (Friedl & Sulla-Menashe, 2015).

Figure 2. Methods workflow showing data used, pre-processing steps and classification inputs and outputs.

Figure 3. Map of detailed land cover classification for Dak Lak, at 10-m resolution.

Figure 4. Closer look at the detailed land cover map in order to highlight specific landscape processes being captured, along with the corresponding satellite images: A) concentration of many new coffee plots, in a sun coffee and rubber landscape in Ea H'Leo, B) establishment of newly planted coffee in M'Drak (Eastern-most district), C) area dominated by sun coffee in Krong Ana, D) high concentration of intercropped or shade coffee near Buon Ma Thuot, E) zoomed in view near Buon Ma Thuot, an area of mixed sun and intercropped plots.

Figure 5. Comparison of A) the binary coffee map from this study; B) the orchard class from the 2017 JAXA Land cover map (10m), derived from S2, Landsat 7 & 8, ALOS/AVNIR-2, PALSAR, and SRTM (Duong et. al., 2018); C) Hurni and Fox's (2018) coffee class from their 2014 boom crop mapping in Mainland Southeast Asia (250m), MODIS-derived; D) Monfreda et al., (2008) "fraction of harvested area," with a threshold of more than 1% coffee area harvested, disaggregated at the 5' (~10km) grid cell from agricultural statistics for 2000.